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ABOUT WIJAR

Westcliff International Journal of Applied Research (WIJAR) is a multidisciplinary, double-blind, peer-reviewed, open-access journal published by the *LITE Center from the Office of Faculty Affairs* in partnership with the *Doctoral Affairs and Academic Resources Department* at Westcliff University. The journal was founded in 2017 and provides an opportunity for academics, industry professionals, and students to publish innovative research that offers insight into practical implementation. In order to widely disseminate new knowledge and scholarship, WIJAR advocates for all submissions to be written in a style that is accessible/available to a broad audience or readership, including those readers who may not be familiar with either research or the topic studied. The journal aligns with Westcliff University's mission to educate, inspire, and empower individuals through its dedication to supporting authors in the review and revision process to produce the highest quality content possible.

Distinguishing this journal from others similar is the strong support offered to contributors, especially first-time authors who may need additional writing or structural assistance. All contributors have access to the Westcliff University Online Writing Center, where dedicated research/writing specialists can offer support and suggestions.

LETTER FROM THE EDITOR-IN-CHIEF

May 2026

I am pleased to share this issue with our readers on behalf of the Editorial Board of the *Westcliff International Journal of Applied Research* (WIJAR). As we celebrate the *10th anniversary* of our journal, this issue holds a special meaning, marking a decade of commitment to academic excellence and applied research. We wish to honor the vision of our founders and the dedication of everyone who has shaped WIJAR into the respected platform it is today.

This issue brings together four articles selected from submissions received in late 2025 and finalized in early 2026. Its publication is the result of the tireless work and dedication behind the review and editorial process. I would like to take this opportunity to thank those who supported its development, ensuring that each contribution reflects the rigor our community expects.

The journal continues to grow thanks to the devotion of its community. Our editorial board, reviewers, and authors all play an essential role in maintaining the quality and relevance of the work we publish. Their time, care, and expertise are deeply valued.

This work reflects our strong commitment to quality. Each article has undergone a careful peer-review and revision process to ensure it meets high academic standards, including clarity, rigor, and strict adherence to APA guidelines.

I invite our readers, faculty, staff, students, and researchers to explore this issue and engage with the ideas it presents. We hope it not only informs your work but also inspires you to consider contributing your own research to WIJAR.

Sincerely,

Mary Allegra
Editor-in-Chief

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The publication of the *Westcliff International Journal of Applied Research* (WIJAR) relies on the contributions of dedicated individuals. We extend our appreciation on behalf of the journal to:

- Dr. Anthony Lee for his unwavering support and strong belief in the journal's significant value for Westcliff University and the wider academic community.
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Thank you all!

Building Socially Aware Machines: The New Frontier of AI Theory of Mind

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Abstract

The research focus was motivated by a curiosity about what lies beyond current artificial intelligence (AI) capabilities and an interest in exploring the next frontier of AI evolution. This research is conducted as a literature review, with the purpose of bringing to light ongoing advances in theory of mind (ToM) AI and outlining future AI directions, specifically for readers who are seeking insights into what's on the horizon in the field of AI. Concretely, the literature review explores the emergence of ToM in AI, tracing its evolution from traditional AI systems towards ToM models capable of comprehending and predicting human mental states. Through a discussion of the current landscape, challenges, and future directions, this literature review clarifies how close AI is to achieving fully-fledged ToM and what's beyond the ultimate realization of ToM. This research reviews recent peer-reviewed sources: empirical and theoretical/conceptual journal articles, review papers, book chapters, conference proceedings, preprints, textbooks, and extended abstracts that were published within the last five years. The findings indicated that ToM in AI is still under development, with its current applications being either in research or experimental phases. Excellent progress was observed in areas such as emotion recognition, predictive modeling, conversational AI, multi-agent systems, simulation, and cognitive modeling. However, constructing mental models with ToM capabilities remains challenging, particularly in leveraging meta-learning to accurately represent existing intelligent entities, whether artificial or human. The conclusion showed that our world still does not fully grasp complex human thoughts, and creating AI systems that can adapt to our ever-changing minds and infer internal mental states is an ambitious milestone beyond which lies self-awareness, a drastic shift in technology that the world may not be ready for.

Keywords: Theory of mind, artificial intelligence, mental models, meta-learning, self-aware AI

Introduction

Artificial intelligence (AI), specifically computer vision, discriminative models, and neural networks (NNs), attracted the public's attention through autonomous vehicle navigation, speech recognition, and complex gaming, respectively (Zhang & Gosline, 2023). With recent advances in generative AI, specifically ChatGPT OpenAI, the public was impressed and more people became familiar with the term "AI," which has been around since 1950 but was less used in daily speech among the public (Zhang & Gosline, 2023; Haenlein & Kaplan, 2019). AI is evolving at a high pace and both scientists and technology researchers are continuously pushing the limits of AI by attempting to mimic human intelligence and feed it into machines (Bhuiyan, 2024). Yet, areas such as self-awareness and theory of mind have not been achieved so far (Nebreda et al., 2024). As of 2025, self-aware AI is hypothetical, whereas the theory of mind is under development (El Qasemy, 2025). Therefore, this review paper will focus on ToM, with the purpose of bringing to light ongoing advances in ToM AI and outlining future AI directions, particularly for readers who are seeking insights into what's on the horizon in the field of AI.

This research is structured as a narrative literature review synthesizing recent peer-reviewed sources, including empirical and theoretical/conceptual journal articles, review papers, book chapters, conference proceedings, preprints, textbooks, and extended abstracts that were published within the last five years. The literature review is organized thematically and was evaluated according to the criteria of accuracy, objectivity, and currency. The inclusion criteria restricted the literature review to studies that shared reliable evidence, maintained a neutral perspective, and reflected the most recent developments in ToM AI.

Definition of Terms

1. Artificial Intelligence: Also referred to as AI, it is the simulation of human intelligence in machines with the purpose of creating AI systems capable of thinking, reasoning, learning, and solving problems with or without explicit human instructions (Sheikh et al., 2023).

2. Computer Vision: A field of artificial intelligence that allows machines to detect and interpret visual information (Szeliski, 2022). Through computer vision, AI systems can successfully perform tasks such as image classification, facial recognition, and scene reconstruction (El Qasemy, 2025).

3. Discriminative Models: A type of machine learning model. It differentiates between the classes of data. For instance, in binary classification, discriminative models define whether an input belongs to class A or B, e.g., logistic regression and support vector machines (Gordon & Hernandez-Lobato, 2020).

4. Neural Networks: A set of computing systems formed by layers of interconnected nodes (Montesinos López et al., 2022). Neural networks are inspired by the human brain, specifically the neurons, and are the foundation of deep learning. Neural networks are efficient in natural language processing and speech recognition (Samek et al., 2021).

5. Generative AI: An AI system that generates content. Generative AI models learn patterns from the data they receive and utilize the knowledge to generate realistic outputs, including images, texts, audio-visual media, and codes (Oluwagbenro, 2024).

6. Meta-learning: The process by which a system learns how to adapt to new tasks or environments more efficiently, using knowledge gained from learning many related tasks (Luo et al., 2022).

7. Theory of Mind: The ability to understand that others have their own thoughts, beliefs, emotions, intentions, perspectives, etc. In AI, the theory of mind implies the creation of machines that can both model and predict human mental states, a level of social-emotional intelligence that's still being developed (Mao et al., 2024).

Discussion

Theory of mind in artificial intelligence is a fascinating multidisciplinary concept that caught the attention of both researchers and scientists. With its multidisciplinary nature tapping into psychology, neuroscience, machine learning, and computer science, ToM is challenging researchers and scientists to convert recognition of human feelings and expressions into understandable computer models for AI agents to rely on. This type of technology is referred to as "emotion recognition technology" and it is advancing in theory, but its application is still infeasible.

ToM in Cognitive Science

Theory of mind is a branch of cognitive science that investigates the cognitive ability of individuals in understanding others' mental states and affirming differences in beliefs, wants, intentions, and internal feelings or emotional behaviors (Hopcroft, 2025). ToM is a psychological skill acquired throughout childhood to allow humans to navigate social interactions and explain or predict their actions or reactions in reference to their personal experiences and drive (Rakoczy, 2022).

ToM in AI

In artificial intelligence, ToM refers to the ability of an AI system to understand, explain, and predict others' mental states, taking into consideration their backgrounds. In this context, others include individuals and AI systems (Mao et al., 2024). Duplicating natural cognitive capabilities in computer science enables achieving human-like AI. Although ToM is still under development, theoretically, it is expected to revolutionize interactions between humans and systems in terms of naturalness and effectiveness (El Qasemy, 2025).

ToM Aspects

Key aspects of ToM in AI involve beliefs, desires, intentions, and emotions (Bamicha & Drigas, 2022). Others may believe in things that are outside the AI's scope of knowledge; this could include cultural customs, religious beliefs, and more. ToM in AI would not only indicate that the AI system will have the capability of understanding that others hold different beliefs from its own but also the capability of recognizing that others have different desires, e.g., goals and drives (Tesar et al., 2020).

From a theoretical perspective, an intelligent system with ToM would be able to predict actions or reactions based on one's intentions in life. In autonomous vehicles, ToM AI could anticipate the intentions of both humans and machines in its environment (Nebreda et al., 2024). ToM AI could also understand emotions and respond accordingly; thus, a deep connection to a human's emotional state would occur in an interaction between the human and the ToM AI system (Bamicha & Drigas, 2022).

Traditional AI Technology and Genuine Comprehension

Traditional AI technology, whether it interacts with humans or not, generates output according to predefined rules and patterns (Aggarwal et al., 2025). For instance, algorithmic trading (AT) is a form of traditional AI focused on automation rather than adaptive learning. It operates through a rule-based system that relies on predefined algorithms and quantitative models to execute profitable trades based on market data, e.g., time, stock price, and volume (Ben Zidane, 2025). In contrast, from a theoretical perspective, ToM AI, while still in progress, is expected to generate output based on a genuine comprehension of its users' psychology: thoughts and emotions, which is a high cognitive process that involves brain connections beyond reasoning (Bamicha & Drigas, 2022).

ToM Instances.

In theory, a ToM robotic aide could detect signs of user fatigue and respond with empathy. Such fatigue could be inferred from non-verbal cues, such as actions and posture, rather than verbal indicators. Another example of ToM in practice could involve a virtual assistant adapting its speech to its interlocutor and enhancing explanations when it notices confusion, showing signs of social awareness (Williams et al., 2022). Building on these examples, intelligent agents with ToM could revolutionize many fields, including educational technology, healthcare, and collaborative robotics (Williams et al., 2022).

Educational Technology.

In the field of education, ToM AI would assess learners' engagement and motivation through multiple reliable educational tools such as emotion-aware learning environments, eye-tracking systems, and physiological sensors. After a full assessment, ToM AI could theoretically interpret behavioral cues as indicators of internal mental states: curiosity, confusion, or frustration (Rosenberg-Kima & Thomas, 2022)

Hypothetical Example.

Hypothetically, a future ToM, an AI-enabled intelligent tutoring system, might use a combination of eye-tracking data, facial expression analysis, and interaction logs from a learning platform to infer that a student is showing signs of disengagement. This includes but is not limited to frequent gaze shifts, reduced interaction time, and expressions of boredom

(Wang et al., 2021; Aly, 2025). Drawing on these inputs, the ToM AI could model the learner's internal state as unmotivated or cognitively overloaded and then adapt the instructional content in real time by simplifying the material, offering encouragement, or switching to a more interactive activity (Sharma et al., 2020). In this scenario, the eye-tracking device, facial recognition software, and platform usage analytics serve as reliable educational tools that feed into the ToM AI's inference system.

ToM in AI: The Design

ToM in AI is still under development; thus, its current applications are either in research or experimental phases. Yet, below is a brief overview of how AI with acquired ToM would proceed:

Step 1: Observing people’s behaviors and communication, specifically nuances of interactions.

Step 2: Saving the information observed and beginning to recognize patterns in thoughts and feelings (Andrews et al., 2023).

The intelligent agent uses its observations and stored information regarding patterns to infer a person’s thoughts and feelings in a specific situation. If its conclusions are inaccurate, then it learns and improves. This process is called machine learning (El Qasemy, 2025).

For consistency and clarity purposes, let’s follow up on the example of the virtual assistant previously shared. In an interaction between a ToM virtual assistant and a person, the ToM virtual assistant could notice short sentences, assume that the person is either busy or not in the mood for long conversations, and would adapt its responses accordingly, e.g., by replacing details with conciseness.

ToM AI Versus Traditional AI

Traditional AI acts or reacts according to the predefined rules and patterns (Aggarwal et al., 2025), while ToM AI is intended to react according to its understanding of its interlocutor’s thoughts and emotions. As of now, ToM AI is still under development; thus, this statement is more of an aim than a reality.

Challenges

Achieving a fully-fledged ToM AI requires major advancements in existing technologies. Genuinely grasping human intelligence might require utilizing neural networks (NNs), which are fundamentally different from the NNs used in limited memory AI. NNs used in limited memory AI rely primarily on historical data to decide the next steps or predict an outcome. These AI systems do not store the data they come across for future development or long-term learning (Aru et al., 2023).

ToM AI developers are encountering many other challenges. At the outset, humans have a mind that’s complex enough to understand, and even if understood, it is changeable. Building a ToM AI that not only understands the human mind but also grasps that it can change based on many factors is not an easy task (Cuzzolin et al., 2020; Wang et al., 2021).

The AI system must also be capable of differentiating between emotions, beliefs, and needs. Not to overlook the fact that the AI system would be expected to interact with a variety of human beings who might be on the spectrum or facing neurological diseases and psychiatric disorders such as dementia and schizophrenia, respectively (Cuzzolin et al., 2020).

Understanding the Human Mind

Perception of emotions and beliefs comes to humans naturally, although it is not always accurate, as affected by personal background and cognitive health status (Tesar et al., 2020). One of the main challenges is developing AI systems that are capable of interpreting cues accurately, whether verbal or non-verbal (Cuzzolin et al., 2020; Wang et al., 2021). This capability is hard to reach even in humans who often times misjudge each other and misread signals. This could be due to differences in maturity levels, emotional intelligence, or social experiences (Tesar et al., 2020). Not only is it challenging to create a ToM AI that understands the human mind, but it also interprets situations accurately in a complex environment where the exact same signals could mean different things to different people.

Constructing Mental Models

Constructing mental models with ToM capabilities requires crafting precise representations of existing intelligent entities, whether artificial or human. The difficulty is in the 'how' (Andrews et al., 2023). How can meta-learning be utilized to construct mental models with ToM? For clarification purposes, meta-learning is a subfield of machine learning focused on enabling models to improve their learning process over time by learning from previous experiences. Thus, meta-learning is also called learning to learn (Vettoruzzo et al., 2024). Instead of training a model just to perform a specific task, meta-learning trains a model to generalize across tasks so it can quickly adapt to new, unseen tasks with minimal data (Vettoruzzo et al., 2024).

Types of Meta-Learning Approaches

There are three types of meta-learning approaches: model-based, metric-based, and optimization-based.

The model-based meta-learning approach designs networks with internal memory, such as long short-term memory networks (LSTMs), to enable rapid adaptation to new data. In contrast, the metric-based approach learns to compare new examples with known ones, as in Siamese networks (Tian et al., 2022), while the optimization-based approach focuses on improving the efficiency of learning better or faster, e.g., model-agnostic meta-learning (MAML) (Vanschoren, 2019).

In theory, meta-learning can help an AI system quickly infer the beliefs or goals of a new agent it has not seen before, just by observing a small amount of behavior; essentially learning how to model minds faster.

Ethical Implications of ToM AI

Theory of mind capabilities could raise important ethical and societal concerns. Intelligent systems that model human cognition could compromise privacy, introduce bias, and unintentionally or deliberately manipulate user behavior (Langley et al., 2022).

Privacy could be compromised through data collection, non-encrypted storage, and interpretation of users' sensitive personal information as a means to make behavioral predictions. While biases could be introduced through perpetuation of societal or cultural inequities. Introduction of biases would be the result of feeding the ToM AI subjective data for training purposes (Langley et al., 2022); thus, the importance of carefully and ethically designing intelligent systems (Edwards, 2024).

Manipulation represents another important ethical implication associated with intelligent systems and can arise when behavior prediction is used to influence decisions of ToM AI users without transparent disclosure (Langley et al., 2022). Manipulation is discussed in detail in the societal implications section of this literature review.

Societal Implications of ToM AI

From a societal perspective, intelligent systems that model human cognition may shape choices, alter the nature of social engagement, and expand machine authority.

Shaping Choices

Prediction of intentions or preferences could affect human decisions in a very subtle manner, shaping choices in many areas, including but not limited to education, healthcare, or consumer decisions, without the user's conscious awareness (Matta, 2026).

Impacts on decision-making processes could either be beneficial or manipulative, depending on how the ToM AI model is designed and how transparent it is. For instance, a positive impact of ToM AI on decision-making in the educational field could involve suggesting interesting resources that would help the user make faster, well-informed decisions. While a negative impact could involve manipulation through neuromarketing techniques and strategic nudging towards products or services, shaping choices in ways that might not be immediately perceptible to users (Chokshi, 2025).

Altering the Nature of Social Engagement

ToM AI could influence human communication and human-to-human collaboration. Equipped with functions such as anticipating needs, providing suggestions, and potentially acting as a social partner, ToM AI might seem all-encompassing or even self-contained. Thus, humans might feel enticed to fully rely on it. Besides full reliance, humans might also replace their human-to-human interactions with human-to-AI interactions or at least mediate or guide existing human-to-human interactions via ToM AI, resulting in a decrease in direct human-to-human interactions and eventually altering the nature of social engagement (Freund, 2023).

Expanding Machine Authority

In theory, a ToM AI could appear socially intelligent, although it may not possess genuine social intelligence. This behavior, although pseudo-social and simulated by predictions of mental states through pattern recognition and probabilistic inference, could overly appeal to humans (Deel et al., 2023). Humans might assume that the said socially intelligent system understands context perfectly and over-trust its recommendations, resulting in full reliance, especially when the performance of the ToM AI aligns with users' expectations. In contrast, a detection of bias or failure from the ToM AI's side could erode human trust and affect potential adoption of general automated systems (Freund, 2023).

Fully-Fledged ToM AI: Feasibility

The analyses of ToM AI feasibility present conflicting conclusions. On one hand, certain studies suggest that despite ToM being a prominent concept, its feasibility is not confirmed and if achieved, ways to verify its reliability must be identified (Wang et al., 2024). On the other hand, researchers, scientists, and technology developers are hinting at ToM being achievable, especially after the recent breakthroughs in technology. Some believe that progress is shaping up, exceptionally after the significant advances observed in large language models such as GPT-4 and LLaMA2. Although these large language models' responses are similar to those of humans, one cannot safely consider human-like responses as an achieved ToM capability. Moreover, although GPT-4 and LLaMA2 seem to understand irony or hints, it is unclear whether this is the route to ToM (Wang, 2023). This conflict in conclusions emphasizes the need for caution, scrutiny, and further testing prior to large-scale implementation.

With increased curiosity and interest, technology enthusiasts are impatiently waiting for what's next, while experts in the field are hitting the brakes and warning against premature machine anthropomorphism (Wang et al., 2024). Several scholars caution that applying human-centered terminology to describe a machine's function could blur the line between human intelligence and artificial intelligence, potentially misleading the public (Wang et al., 2021). The world may not be ready yet for this drastic shift in technology and we should carefully examine when it would be appropriate to make it happen because, beyond the ultimate realization of ToM, there will be self-awareness, the latest and greatest stage of AI development.

ToM AI Versus Self-Aware AI

Based on theoretical research, ToM AI could model the mental states of other agents, human or artificial, and then use that model to predict or explain the agent's behavior. Mental states involve beliefs, desires, intentions, and knowledge. This is a much more advanced cognitive capability than current AI generally has (Li et al., 2025).

Self-aware AI could recognize its existence as a non-human subject, act or react based on ethics, and could feel empathy (Shi et al., 2025; Khusainova & Filippova, 2022). However, existing theory posits that this form of empathy is expected to be cognitive rather than emotional (Khusainova & Filippova, 2022). Technology facilitating the achievement of self-awareness in AI is not available at the moment and whether it will ever be remains debatable.

Recommendations

Cross-disciplinary research combining insights from cognitive science, psychology, computer science, and most importantly, ethics is highly recommended to support designing robust, responsible, and socially responsive ToM models in AI. Empirical validation in real-world settings is also recommended to not only assess the effectiveness or reliability but also further identify any additional ethical implications of AI systems with ToM capabilities in practice. Building on ToM, future research may turn to self-awareness, the next frontier in AI development.

Conclusion

Traditional AI follows fixed rules and provides an already set output for a given input. Thus, there is no genuine comprehension of thoughts or emotions in the process. Contrary to traditional AI, theory of mind AI strives to fully perceive subtle human thoughts and feelings and react accordingly. Although ToM AI is still under development, excellent progress is observed in areas such as emotion recognition, predictive modeling, conversational AI, simulation and cognitive modeling, and multi-agent systems. These breakthroughs are a step towards an AI that does not complete tasks solely but understands the agent it works with. Yet, full practical feasibility remains uncertain, and if achieved, ways to verify reliability must be identified.

Achieving a fully fledged ToM AI requires substantial technology, including sophisticated neural networks and meta-learning approaches capable of modeling the complexity, variability, and evolving nature of the human mind. A fully fledged ToM AI should distinguish among emotions, beliefs, and needs while accurately interpreting verbal and nonverbal cues across diverse individuals and contexts, an ability that even humans find challenging to achieve. Beyond these technical challenges, the development of ToM AI raises significant ethical and societal concerns, including privacy risks, bias, and behavioral manipulation, along with broader impacts on shaping human choices, altering social engagement, and expanding machine authority. The world might not be ready for this drastic shift in technology and experts caution against premature machine anthropomorphism. This research matters because our world still does not fully understand human thoughts and is nonetheless expected to create AI systems that can adapt to our ever-changing minds and/or distinguish between various mental states: thoughts versus feelings, bearing in mind that internal states are unobservable and rather inferred.

References

Aggarwal, R., Sachan, S., Verma, R., & Dhanda, N. (2025). Traditional AI vs. modern AI. In A. Sharma, Nayancy, & R. Verma (Eds.), *The confluence of cryptography, blockchain and artificial intelligence* (pp. 51–75). CRC Press. https://doi.org/10.1201/9781032711515

Aly, M. (2025). Revolutionizing online education: Advanced facial expression recognition for real-time student progress tracking via deep learning model. *Multimedia Tools and Applications, 84*(13), 12575-12614. https://doi.org/10.1007/s11042-024-19392-5

Andrews, R. W., Lilly, J. M., Srivastava, D., & Feigh, K. M. (2023). The role of shared mental models in human-AI teams: a theoretical review. *Theoretical Issues in Ergonomics Science, 24*(2), 129-175. https://doi.org/10.1080/1463922X.2022.2061080

Aru, J., Labash, A., Corcoll, O., & Vicente, R. (2023). Mind the gap: Challenges of deep learning approaches to theory of mind. *Artificial Intelligence Review, 56*(9), 9141-9156. https://doi.org/10.1007/s10462-023-10401-x

Bamicha, V., & Drigas, A. (2022). The evolutionary course of theory of mind factors that facilitate or inhibit its operation & the role of ICTs. *Technium Social Sciences Journal. 30,* 138-158. https://doi.org/10.47577/tssj.v30i1.6220

Ben Zidane, M. (2025). Stock price and volume volatility of mergers and acquisitions companies. *Westcliff International Journal of Applied Research, 9*(2), 5-11. https://doi.org/10.47670/wuwijar20252MZ

Bhuiyan, M. M. (2024, June 3). The illusion of boundless AI: Analyzing limitations and ethical concerns. [Preprint]. TechRxiv. https://doi.org/10.36227/techrxiv.171742375.53309794/v1

Chokshi, S. (2025). The ethics of AI nudges: How AI influences decision-making. *Asian Management Insights, 12*(1), 84–91. https://ink.library.smu.edu.sg/ami/278

Cuzzolin, F., Morelli, A., Cirstea, B., & Sahakian, B. J. (2020). Knowing me, knowing you: Theory of mind in AI. *Psychological Medicine, 50*(7), 1057-1061. https://doi.org/10.1017/S0033291720000835

Deel, G., Cain, C., & Cain, L. (2023). Ethical considerations for the future of superhuman artificial intelligence: A viewpoint. *Robonomics: The Journal of the Automated Economy, 4*, 41-41. https://journal.robonomics.science/index.php/rj/article/view/41

Edwards, H. (2024). Toward Ethical AI: Relational Dynamics, Theory of Mind, and Human-Compatible Artificial Intelligence. *Contexts, 1*(5).

El Qasemy, H. (2025). Cognitive technologies: Machine learning, artificial intelligence, and convolutional neural networks in computer vision. Westcliff International *Journal of Applied Research, 9*(1), 5-17. https://doi.org/10.47670/wuwijar20251HEQ

Freund, L. (2023). Exploring the Intersection of Rationality, Reality, and Theory of Mind in AI Reasoning: An Analysis of GPT-4's Responses to Paradoxes and ToM Tests [Preprint].PhilArchive. https://philarchive.org/rec/LUCPAT-6

Gordon, J., & Hernandez-Lobato, J. M. (2020). Combining deep generative and discriminative models for Bayesian semi-supervised learning. *Pattern Recognition*, 100, 107156. https://doi.org/10.1016/j.patcog.2019.107156

Haenlein, M., & Kaplan, A. (2019). A brief history of artificial intelligence: On the past, present, and future of artificial intelligence. *California Management Review*, *61*(4), 5-14. https://doi.org/10.1177/0008125619864925

Hopcroft, R. L. (2025). Neurosociology and theory of mind (ToM). In W. Kalkhoff, J. Dippong, & R. B. Firat (Eds.), *Handbook of neurosociology* (pp. 269–281). *Springer.* https://doi.org/10.1007/978-3-031-95615-7_15

Khusainova, F., & Filippova, V. (2022). Self-awareness of artificial intelligence: Scoping review. *Global and Regional Research, 4*(2), 118–125.

Langley, C., Cirstea, B. I., Cuzzolin, F., & Sahakian, B. J. (2022). Theory of mind and preference learning at the interface of cognitive science, neuroscience, and AI: A review. *Frontiers in artificial intelligence*, *5*, 778852. https://doi.org/10.3389/frai.2022.778852

Li, X., Shi, H., Xu, R., & Xu, W. (2025). AI Awareness [Preprint]. ArXiv. https://doi.org/10.48550/arXiv.2504.20084

Luo, S., Li, Y., Gao, P., Wang, Y., & Serikawa, S. (2022). Meta-seg: A survey of meta-learning for image segmentation. *Pattern Recognition, 126*, 108586. https://doi.org/10.1016/j.patcog.2022.108586

Mao, Y., Liu, S., Ni, Q., Lin, X., & He, L. (2024). A review on machine theory of mind. *IEEE Transactions on Computational Social Systems, 11*(6), 7114–7132. https://doi.org/10.1109/TCSS.2024.3416707

Matta, D. (2026). Artificial intelligence and theory of mind. *Journal of Psychology and AI,* (21), 2628373. https://doi.org/10.1080/29974100.2026.2628373

Montesinos López, O. A., Montesinos López, A., & Crossa, J. (2022). Fundamentals of artificial neural networks and deep learning. In O. A. Montesinos López, A. Montesinos López, & J. Crossa (Eds.), *Multivariate statistical machine learning methods for genomic prediction* (pp. 379–425). Springer International Publishing. https://doi.org/10.1007/978-3-030-89010-0_10

Nebreda, A., Shpakivska-Bilan, D., Camara, C., & Susi, G. (2023). The social machine: Artificial intelligence (AI) approaches to theory of mind. In T. Lopez-Soto, A. Garcia-Lopez, & F. J. Salguero-Lamillar (Eds.), *The theory of mind under scrutiny* (pp. 681–722). Springer. https://doi.org/10.1007/978-3-031-46742-4_22https://doi.org/10.1007/978-3-031-46742-4_22

Oluwagbenro, M. B. (2024). Generative AI: Definition, concepts, applications, and future prospects. [Preprint]. TechRxiv. https://doi.org/10.36227/techrxiv.171746875.59016695/v1

Rakoczy, H. (2022). Foundations of theory of mind and its development in early childhood. *Nature Reviews Psychology, 1*(4), 223-235. https://doi.org/10.1038/s44159-022-00037-z

Rosenberg-Kima, R. B., & Thomas, A. (2022). A teacher without a soul? Social-AI, theory of mind, and consciousness of a robot tutor. In M. M. Rodrigo, N. Matsuda, A. I. Cristea, & V. Dimitrova (Eds.), *Artificial intelligence in education* (pp. 240–244). https://doi.org/10.1007/978-3-031-11647-6_43

Samek, W., Montavon, G., Lapuschkin, S., Anders, C. J., & Müller, K. R. (2021). Explaining deep neural networks and beyond: A review of methods and applications. *Proceedings of the IEEE, 109*(3), 247–278. https://doi.org/10.1109/JPROC.2021.3060483

Sharma, K., Giannakos, M., & Dillenbourg, P. (2020). Eye-tracking and artificial intelligence to enhance motivation and learning. *Smart Learning Environments, 7*(1), 13. https://doi.org/10.1186/s40561-020-00122-x

Sheikh, H., Prins, C., & Schrijvers, E. (2023). Artificial intelligence: Definition and background. In *Mission AI: The new system technology* (pp. 15–41). Springer International Publishing. https://doi.org/10.1007/978-3-031-21448-6_2

Shi, H., Yin, B., Teng, L., & Ma, B. (2025). Empathetic AI encounters: Pathways to prosocial behavior. *Journal of Service Research*, Advance online publication. https://doi.org/10.1177/109467052513805

Szeliski, R. (2022). *Computer vision: Algorithms and applications* (2nd ed.). Springer Nature.

Tesar, B., Deckert, M., Schmoeger, M., & Willinger, U. (2020). Electrophysiological correlates of basic and higher order cognitive and affective theory of mind processing in emerging and early adulthood - An explorative event-related potentials study to investigate first, second, and third-order theory of mind processing based on visual cues. *Frontiers in Human Neuroscience, 14*, 79. ttps://doi.org/10.3389/fnhum.2020.00079

Tian, Y., Zhao, X., & Huang, W. (2022). Meta-learning approaches for learning-to-learn in deep learning: A survey. *Neurocomputing, 494*, 203-223. https://doi.org/10.1016/j.neucom.2022.04.078

Vettoruzzo, A., Bouguelia, M. R., Vanschoren, J., Rögnvaldsson, T., & Santosh, K. C. (2024). Advances and challenges in meta-learning: A technical review. *IEEE Transactions on Pattern Analysis and Machine Intelligence, 46*(7),4763–4779. https://doi.org/10.1109/TPAMI.2024.33578475

Vettoruzzo, A., Bouguelia, M. R., Vanschoren, J., Rögnvaldsson, T., & Santosh, K. C. (2024). Advances and challenges in meta-learning: A technical review. *IEEE transactions on pattern analysis and machine intelligence, 46*(7), 4763-4779. https://doi.org/10.1109/TPAMI.2024.3357847

Wang, J. (2023). Self-awareness: A singularity of AI. *Philosophy, 1*3(2), 68-77. https://doi.org/10.17265/2159-5313/2023.02.003

Wang, Q., Saha, K., Gregori, E., Joyner, D., & Goel, A. (2021). Towards mutual theory of mind in human-AI interaction: How language reflects what students perceive about a virtual teaching assistant. In *Proceedings of the CHI Conference on Human Factors in Computing Systems* (pp. 1–14). https://doi.org/10.1145/3411764.3445645

Wang, Q., Walsh, S., Si, M., Kephart, J., Weisz, J. D., & Goel, A. K. (2024). Theory of mind in human-AI interaction. In *Extended abstracts of the CHI Conference on Human Factors in Computing Systems* (pp. 1–6). https://doi.org/10.1145/3613905.3636308

Williams, J., Fiore, S. M., & Jentsch, F. (2022). Supporting artificial social intelligence with theory of mind. *Frontiers in Artificial Intelligence, 5*, 750763. https://doi.org/10.3389/frai.2022.750763

Zhang, Y., & Gosline, R. (2023). Human favoritism, not AI aversion: People's perceptions and bias toward generative AI, human experts, and human–GAI collaboration in persuasive content generation. *Judgment and Decision Making, 18*, e41. https://doi.org/10.1017/jdm.2023.37

AI-Based Customer Behavior Prediction in Banking and Insurance: An Applied Study

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Abstract

Financial institutions can operate under capacity and legal limits by using customer behavior prediction to detect anomalous activity, reduce attrition, and personalize services. Using transactional, relational, and demographic characteristics from a de-identified banking and insurance dataset with 120,000 customers observed over a 24-month period, this study creates and assesses an applied machine-learning framework that forecasts four customer outcomes: product uptake, churn risk, claim propensity, and fraud risk. Temporal, behavioral, and engagement indicators such as tenure, product mix, customer-provider network features, and recency-frequency-monetary (RFM) measurements were generated through feature engineering. Logistic Regression, Random Forest, XGBoost, and a stacked ensemble with a logistic meta-learner trained on out-of-fold predictions are among the models that are compared. MAUC, PR-AUC, precision, recall, F1, Brier score, and calibration curves were used to assess model performance on a temporally separated holdout set. The stacked ensemble produced the best overall performance (average AUC ≈ 0.91 and average PR-AUC ≈ 0.64 across tasks) and well-calibrated probabilities (average Brier score ≈ 0.07). Predictions at the cohort and individual levels were interpreted using SHAP explanations, which showed that relative monetary activity, tenure, and recent engagement frequency were consistently the best predictors for all four outcomes. Targeted interventions based on estimated probabilities may boost cross-sell conversion by around 18% and lower churn by about 12%, according to a deployment simulation with basic cost assumptions while enabling fraud and claims teams to reduce manual review volumes by roughly 30-40% at recall levels over 65% and precision levels above 60%. In order to enhance client outcomes and operational efficiency while adhering to explainable AI and governance standards, the study presents a workable, comprehensible pipeline that financial institutions can incorporate into decision workflows.

Keywords: Customer behavior, predictive analytics, ensemble learning, SHAP, banking, insurance, uplift

Introduction

Financial institutions increasingly rely on data-driven systems to determine where potential fraud may arise, whom to target for new products, which clients to retain, and which claims to prioritize for investigation. By forecasting multiple customer outcomes from historical behavior, modern machine learning enables proactive, targeted interventions that enhance both risk management and customer experience. Nonetheless, the adopted workflows and models in banking and insurance are constrained by three practical requirements: predictions must be interpretable and compliant with regulatory expectations, must integrate smoothly into existing operational workflows and must remain reliable as customer behavior and market conditions evolve.

Prior research demonstrates that ensemble and boosting methods, such as Random Forest and gradient boosting, achieve strong performance in applications including credit scoring, churn prediction, and fraud detection (Ngai et al., 2011; Verbeke et al., 2011; Zhang et al., 2022). However, most studies address only a single task and devote limited attention to probability calibration or real-world deployment effects. At the same time, regulators and industry bodies increasingly emphasize explainable AI, fairness, and rigorous outcomes monitoring in credit, insurance, and other customer-treatment decisions, underscoring the need for models that can be justified to internal stakeholders and external supervisors alike. This combination of factors creates a gap for operationally oriented pipelines that couple high predictive accuracy with transparent explanations, explicit cost-benefit analysis, and well-defined integration points into business processes.

This study addresses that gap by developing a unified customer behavior prediction pipeline for a hybrid banking–insurance context, spanning four linked operational tasks: product uptake, churn, claim propensity, and fraud risk. The approach combines domain-informed feature engineering from transaction and interaction histories, a stacked ensemble that integrates Random Forest and XGBoost through a logistic meta-learner, and SHAP-based interpretability at both global and local levels. Each task k ∈ {uptake, churn, claim, fraud} is formulated as estimating P(Y□ = 1 | X□), where X□ represents customer behavior up to time t. X□ summarizes customer behavior up to time t, and labels are defined on future horizons to avoid temporal leakage. The study's objectives are threefold: to evaluate model performance across the four tasks using discrimination, calibration, and precision–recall–based metrics, to demonstrate actionable interpretability that supports decision-makers in marketing, retention, and risk functions, and to quantify operational impact through a deployment simulation under realistic capacity and cost constraints.

Literature Review

Predictive Analytics in Banking and Insurance

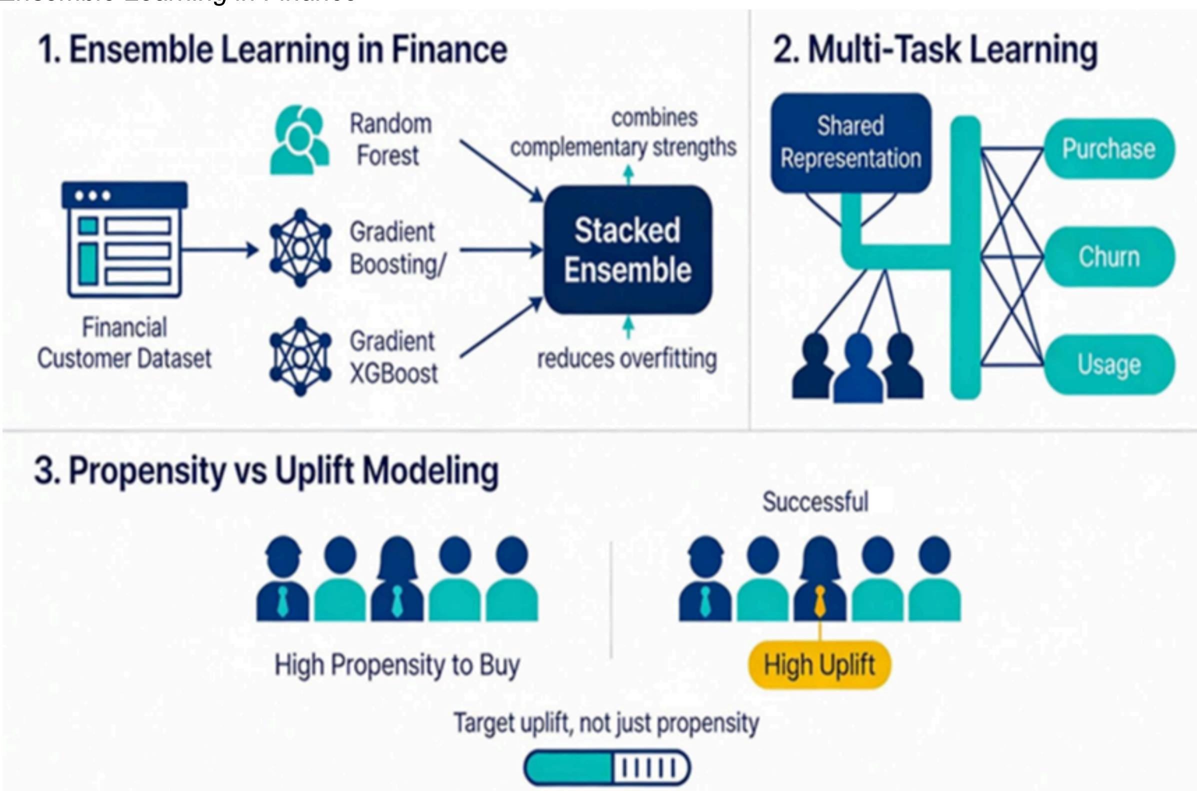
Predictive analytics has a long history in finance, starting with scorecard-based logistic models for credit risk and evolving toward tree ensembles and gradient boosting for complex nonlinear decision problems (Friedman, 2001; Agarwal et al., 2023). In banking, machine learning has been widely applied to credit scoring, default prediction, and customer churn, with Random Forest and gradient boosting often outperforming linear baselines on tabular behavioral data (Zhang et al., 2022; Verbeke et al., 2011). In insurance, predictive models support claim frequency and severity estimation, fraud detection, and underwriting decisions, with recent work exploring advanced feature engineering and time-series representations from claims histories and telematics data (Ngai et al., 2011; Zhou et al., 2021).

Customer churn prediction in digital banking commonly uses transactional and engagement features to identify at-risk customers, with studies reporting that tree-based models provide high AUC and robustness to heterogeneous data (Verbeke et al., 2011; Zhang et al., 2022). Fraud detection and claims triage often require handling extreme class imbalance and evolving adversarial behavior, which motivates the use of ensemble methods, anomaly detection techniques, and hybrid rule-based and machine learning systems (Ngai et al., 2011; Zhou et al., 2021). Across these domains, a recurring theme is that domain-informed feature engineering, including recency, spending behavior, and relational indicators, often contributes as much to performance improvement as the selection of model families (Agarwal et al., 2023).

Explainable AI, Ensemble Learning, and Multi-Task Perspectives

In structured financial datasets, including credit scoring, marketing response, and fraud detection tasks, ensemble techniques like Random Forest and gradient boosting (e.g., XGBoost) have consistently demonstrated high performance. When trained via out-of-fold stacking procedures, stacked ensembles, which integrate basic learners through a meta-model, can mitigate overfitting while utilizing complementary characteristics, such as the resilience of Random Forest and the fine-grained decision boundaries of XGBoost. While multi-task implementations in regulated financial settings are still relatively uncommon, recent work in customer base analysis and multi-task customer prediction examines learning shared representations across related outcomes, such as purchase, churn, and product usage. Figure 1 can illustrate the temporal setup, showing the feature window, outcome horizon, and the chronological train–test partition.

Figure 1
Ensemble Learning in Finance



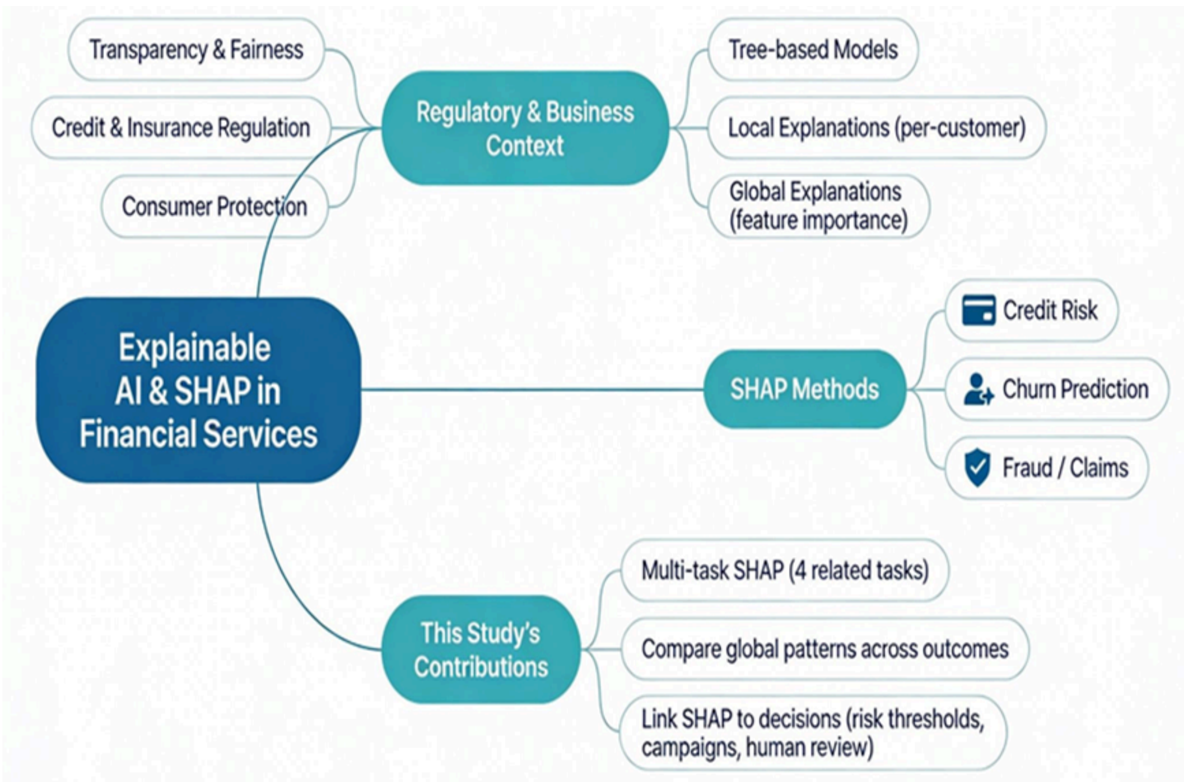
By measuring the incremental effect of treatments, uplift modeling and causal techniques extend propensity models in marketing and consumer analytics, which can further enhance treatment allocation and campaign ROI. Targeting clients with high anticipated uplift rather than high propensity can greatly increase conversion efficiency, according to a number of uplift modeling frameworks for financial services. The deployment simulation is intended to approximate intervention value under capacity restrictions and serves as a basis for future uplift-based extensions, even though this work employs propensity-based probabilities rather than complete uplift models.

Explainable AI and SHAP in Financial Services

Explainable AI is a central requirement for deploying machine learning in credit, insurance, and broader financial decision-making, fueled by regulatory and consumer protection expectations around transparency and fairness

(Doshi-Velez & Kim, 2017; Molnar, 2022). SHAP (SHapley Additive exPlanations) has emerged as a widely used approach for local and global explanation in tree-based models (Lundberg & Lee, 2017), including credit risk, churn, and fraud applications. Ribeiro et al. (2016), in a study about explainable credit risk assessment and churn predictions, show that SHAP can highlight key drivers, such as utilization ratios, payment behavior, or recent engagement, thereby supporting both compliance documentation and business interpretation (see Figure 2).

Figure 2
Explainable AI & SHAP in Financial Services

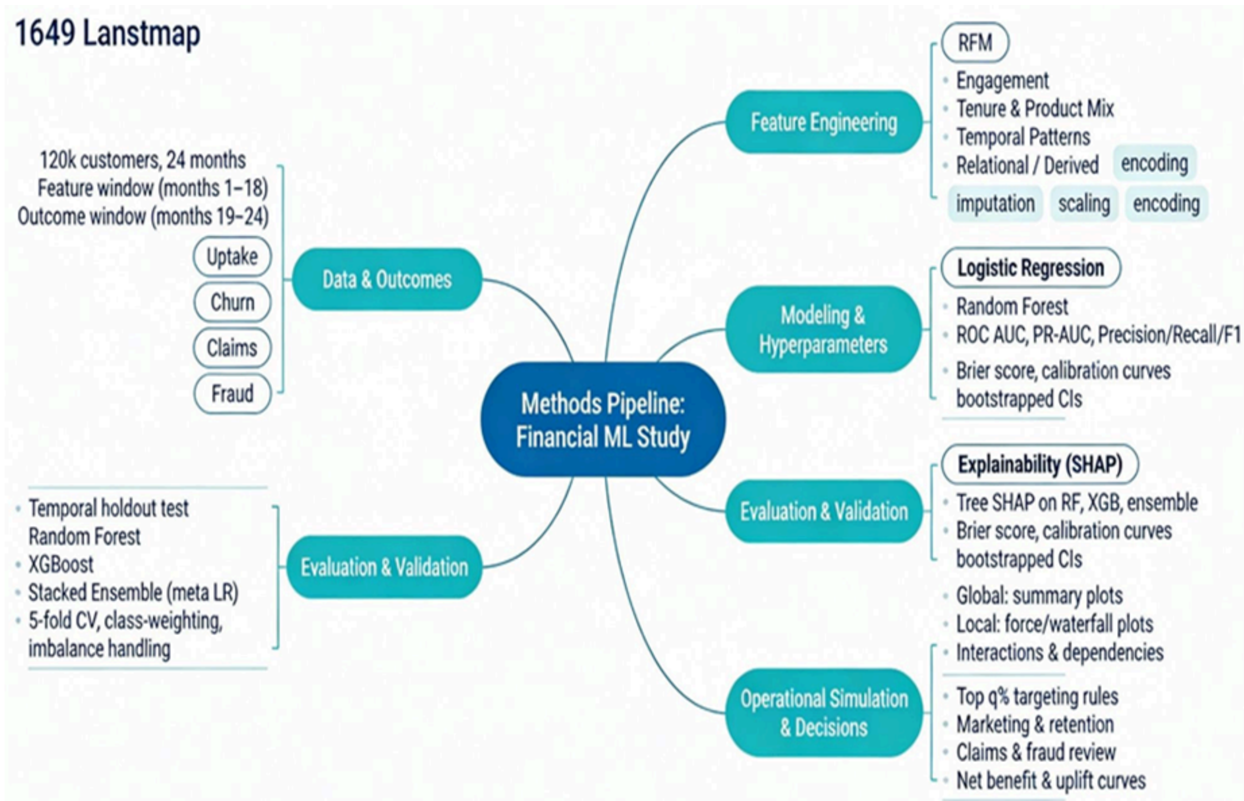


However, many existing works apply SHAP post hoc to a single task and do not systematically link SHAP insights to operational decisions such as risk thresholds, campaign design, or human review workflows. This study builds on the SHAP literature by applying SHAP across four related financial tasks, comparing global feature importance patterns across outcomes, and integrating local explanations into a deployment scenario for product marketing, retention, and fraud/claims investigation.

Methods and Materials

This study develops an end-to-end machine learning pipeline for financial modeling, from temporally structured customer data and engineered feature families through multi-model training with SHAP explainability to decision-focused deployment simulations across four financial tasks (see Figure 3).

Figure 3
Methods Pipeline



Data and Outcome Definitions

The dataset consists of 120,000 de-identified customers from a mid-sized financial institution offering retail banking and insurance products, observed over 24 consecutive months. For each customer, monthly aggregates include transactional summaries (deposits, withdrawals, card spend), product holdings (loans, savings, cards, insurance), interaction logs (digital logins, branch visits, call center contacts), and basic demographic attributes (age band, region, and customer segment). All personally identifiable information (PII) was removed, and the institution granted written authorization for academic use; no interventions were conducted, so institutional review board procedures were not required.

To avoid temporal leakage, the 24-month period is split into a feature window and an outcome window, a common practice in predictive modeling for financial time-series data (Zhang et al., 2022). Customer features are computed using data from months 1–18, and outcomes are defined over months 19–24, with the train/validation/test split respecting chronological order. A typical split uses customers with earlier histories for training and validation and reserves the latest cohort for the holdout test, ensuring that evaluation reflects forward-looking performance under realistic conditions (Agarwal et al., 2023).

Four binary outcomes are defined:

- Product uptake: Whether a customer accepts an offered banking or insurance product within 90 days after a campaign starts in the outcome window, consistent with response modeling approaches in financial services (Zhang et al., 2022).
- Churn: Whether the primary account is closed or activity ceases for at least six consecutive months in the outcome window, following common definitions in customer retention studies (Verbeke et al., 2011).
- Claim propensity: Among insurance customers, whether at least one claim is filed in the subsequent 12 months, aligned with predictive analytics approaches in insurance risk modeling (Ngai et al., 2011).
- Fraud risk: Whether any claim or transaction is flagged and subsequently confirmed as fraudulent in the outcome window, consistent with machine learning–based fraud detection frameworks (Zhou et al., 2021; Chambugong et al., 2025).

A summary of these results reports on the number of customers, positive rate, and task-specific subsets for each outcome. As shown in the data, fraud is rare (≈3–5%), and claim propensity is moderately imbalanced (≈8–12%), whereas product uptake has a significantly higher event rate (see Figure 4).

Figure 4
Outcome Summary

Feature Engineering

Features are grouped into five families, following common practices in financial predictive analytics and customer behavior modeling (Agarwal et al., 2023; Zhang et al., 2022):

- Recency–Frequency–Monetary (RFM): Monetary features include average and total monthly spend, deposits, and withdrawals over rolling windows of 3, 6, and 12 months, widely used in customer analytics (Ngai et al., 2011).

- Frequency features: Number of transactions, distinct merchants/providers, and card swipes per month, aggregated over 3–12 months, capturing behavioral intensity (Verbeke et al., 2011).

- Recency indicators: Measure the time elapsed since the last transaction and include transformed metrics such as $R_{90}=\exp(-\Delta t_{\text{last txn}}/90)$ R_{90} = \exp(-\Delta t_{\text{last txn}} / 90) $R_{90}=\exp(-\Delta t_{\text{last txn}}/90)$, to emphasize recent activity and behavioral decay patterns.

- Engagement: Digital interactions such as login counts, mobile versus web usage, and days active in the last 30–90 days, reflecting customer engagement levels (Zhang et al., 2022).

- Physical interactions: Branch visits, call center contacts, and complaint records, capturing offline engagement behavior.

- Engagement mix: Ratios of digital to total interactions and the number of product-related interactions (e.g., viewing loan offers), indicating customer interest and responsiveness.

- Tenure and product mix: Account tenure measured as months since first account opening and since last product addition, along with product mix features such as number of active products, maximum product tier, and multi-product relationship indicators, which are known to influence retention and cross-selling outcomes (Verbeke et al., 2011).

Temporal patterns:

- Seasonality indicators: Month-of-year and quarter flags, along with indicators capturing seasonal behavior patterns in financial activity.

- Trend features: Slopes derived from linear regressions of monthly balances or transaction volumes over the last 12 months, capturing increasing or declining engagement and monetary activity (Agarwal et al., 2023).

- Relational and derived features:

- Claim-level ratios: Ratio of historical claim amounts to policy limits, prior claim counts, and average claim severity for claim propensity and fraud tasks, commonly used in insurance analytics (Ngai et al., 2011).

- Network-style features: Counts or simple scores derived from customer–provider co-occurrence graphs (e.g., number of providers also associated with past fraud), capturing relational risk patterns (Zhou et al., 2021), constructed strictly from pre-outcome history to prevent leakage.

Missing numerical values are imputed with the median, and categorical variables (such as region or product tier) with the mode. Continuous features are standardized as needed for model stability in logistic regression and for regularization-friendly interpretability in the meta-learner. For high-cardinality categories (e.g., providers) used in relational features, frequency or target encoding is applied in a cross-validated manner to reduce dimensionality without introducing strong leakage.

Modeling and Hyperparameters

Four model families are trained separately for each outcome:

- Logistic Regression: A baseline linear classifier with L2 regularization and class-weighted cross-entropy loss, commonly used in financial risk modeling due to its interpretability (Agarwal et al., 2023).
- Random Forest: An ensemble of decision trees with tuned parameters, including number of trees (100–300), maximum depth (4–12), and max_features for split selection, known for robustness in handling structured financial data (Verbeke et al., 2011).
- XGBoost: A gradient boosting framework with a tree-based booster, widely adopted for high-performance modeling on tabular datasets (Chen & Guestrin, 2016), with tuned hyperparameters including learning rate (0.03–0.2), maximum depth (3–8), number of estimators (100–400), subsample ratio, and column subsampling rates.
- Stacked Ensemble: Random Forest and XGBoost serve as level-0 base learners, while their out-of-fold predicted probabilities are used as input features for a level-1 logistic regression meta-learner, enabling improved generalization through model combination (Friedman, 2001).

Hyperparameters are tuned using 5-fold stratified cross-validation on the training set, optimizing ROC AUC for each task separately, a standard approach in machine learning model selection (Zhang et al., 2022). For stacking, a K-fold stacking protocol is applied: for each fold, base learners are trained on the remaining folds and generate out-of-fold predictions for the held-out fold; the concatenation of these predictions forms the meta-learner training set, helping to reduce overfitting and improve predictive stability (Friedman, 2001).

Evaluation Metrics and Validation

Models are evaluated on a held-out test set consisting of customers from the most recent time segment, with stratification by outcome to preserve event rates. This approach ensures realistic forward-looking evaluation in financial prediction tasks (Agarwal et al., 2023). For each task and model, the following metrics are computed:

- ROC AUC: Measures overall discrimination across thresholds and is widely used in classification problems (Zhang et al., 2022).
- PR-AUC: Precision–recall area under the curve, particularly informative for imbalanced outcomes such as fraud and claims (Zhou et al., 2021).
- Precision, recall, F1: Evaluated at chosen operating thresholds tailored for each task, supporting decision-focused evaluation (Verbeke et al., 2011).
- Brier score: Mean squared error between predicted probabilities and observed outcomes, capturing calibration quality (Agarwal et al., 2023).
- Calibration curves: Reliability diagrams comparing predicted and empirical event rates in probability bins, used to assess probability calibration (Zhang et al., 2022).

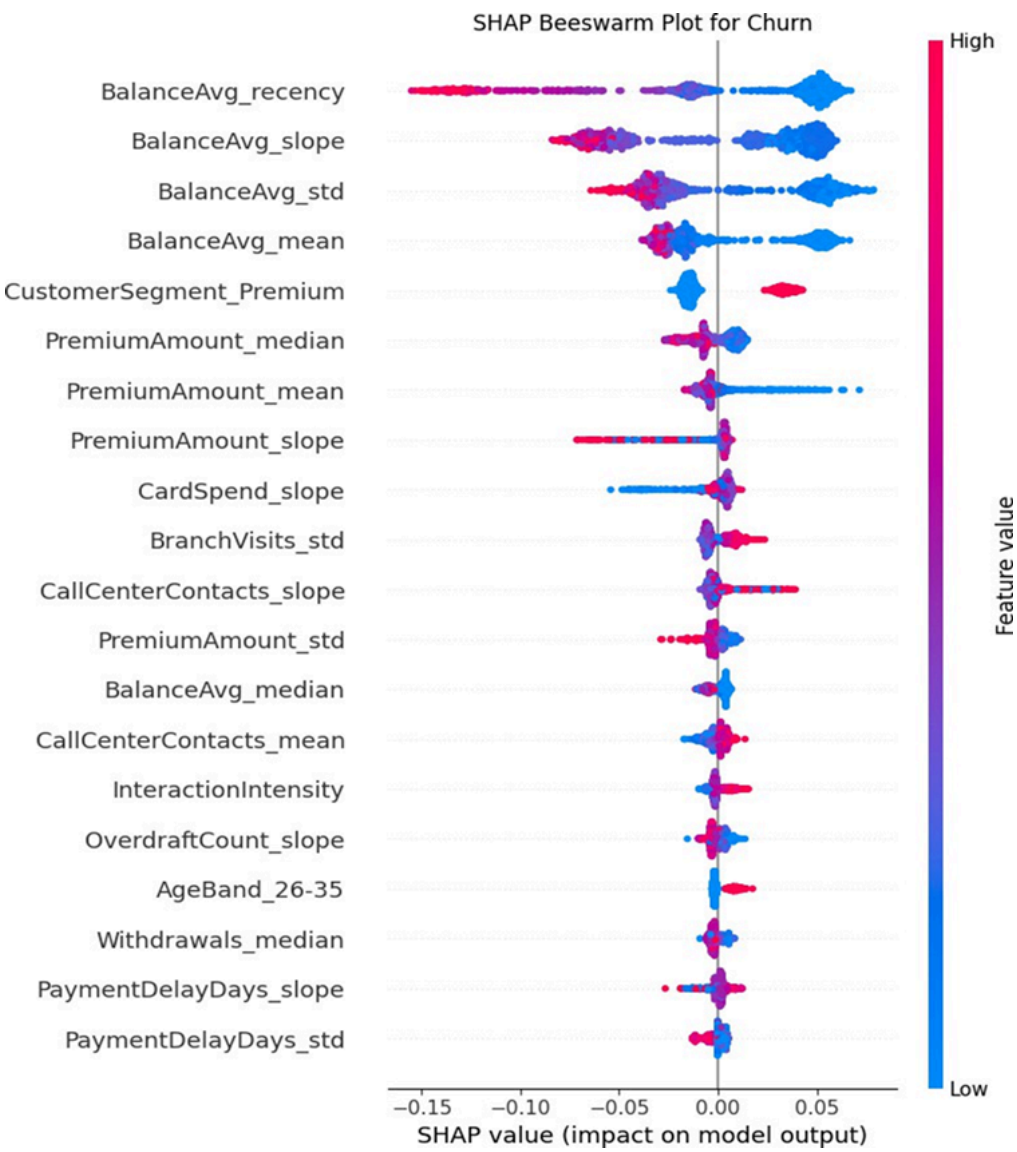
Thresholds for reporting precision, recall, and F1 are selected based on operational objectives and are later reused in the deployment simulation. To assess robustness, results are averaged over multiple random seeds for data splits and model initialization, and confidence intervals for AUC are estimated via bootstrapping, a common practice in machine learning evaluation (Friedman, 2001).

Explainable AI and SHAP Analysis

SHAP values are computed for tree-based models and the stacked ensemble using efficient tree-based SHAP algorithms (Lundberg & Lee, 2017). Global explanations are generated through SHAP summary plots, which display both feature importance and the direction of feature effects across the customer population for each task (Molnar, 2022). As shown in Figure 5, the SHAP beeswarm plot for churn illustrates variables such as balance recency and slope impact model output.

Local explanations are produced using SHAP waterfall or force plots for individual customers, illustrating how each feature contributes to shifting the prediction away from the baseline risk. Such local interpretability methods help explain individual model decisions and support transparency in complex machine learning systems (Ribeiro et al., 2016).

Figure 5
SHAP Value: Impact on Model



For comparability, SHAP analyses focus on the final stacked ensemble models, though results for XGBoost alone are examined to ensure alignment. SHAP interaction values and dependency plots are also explored for key feature pairs, such as interactions between tenure and engagement or between monetary activity and product mix.

Operational Simulation and Decision Rules (Revised)

The following operational scenarios illustrate how the model outputs can be translated into practical decision rules across different use cases:

- To translate model performance into measurable business impact, a deployment simulation framework is developed to define decision rules based on predicted probabilities and simplified cost–benefit assumptions. For each predictive task, customers or transactions are prioritized according to model-estimated risk or propensity scores, enabling targeted and resource-efficient interventions (Agarwal et al., 2023).

- For product uptake, customers within the top q% of predicted purchase probability are selected for targeted marketing campaigns, where q varies across scenarios (e.g., 10%, 15%, and 20%) to reflect different outreach capacities. This approach aligns with predictive targeting strategies used in customer analytics (Zhang et al., 2022).

- For churn prediction, customers within the top q% of predicted churn risk are targeted with retention strategies, such as fee waivers, loyalty incentives, or personalized offers, aimed at reducing attrition (Verbeke et al., 2011).

- For claim propensity, high-risk insurance customers are identified and flagged for proactive engagement or policy review, supporting early intervention and improved risk management (Ngai et al., 2011).

- For fraud risk, claims or transactions within the top q% of predicted fraud probability are prioritized for manual investigation, subject to operational constraints such as review capacity and investigation cost (Zhou et al., 2021; Chambugong et al., 2025).

- This simulation framework enables the evaluation of trade-offs between precision, recall, operational workload, and expected financial outcomes, providing actionable insights for decision-makers across marketing, retention, and risk management functions (Agarwal et al., 2023). The financial trade-offs and net benefits of these operational strategies are visualized in the uplift curves for churn (Figure 6) and policy lapse prediction (Figure 7).

Figure 6
Uplift Curve for Churn Prediction

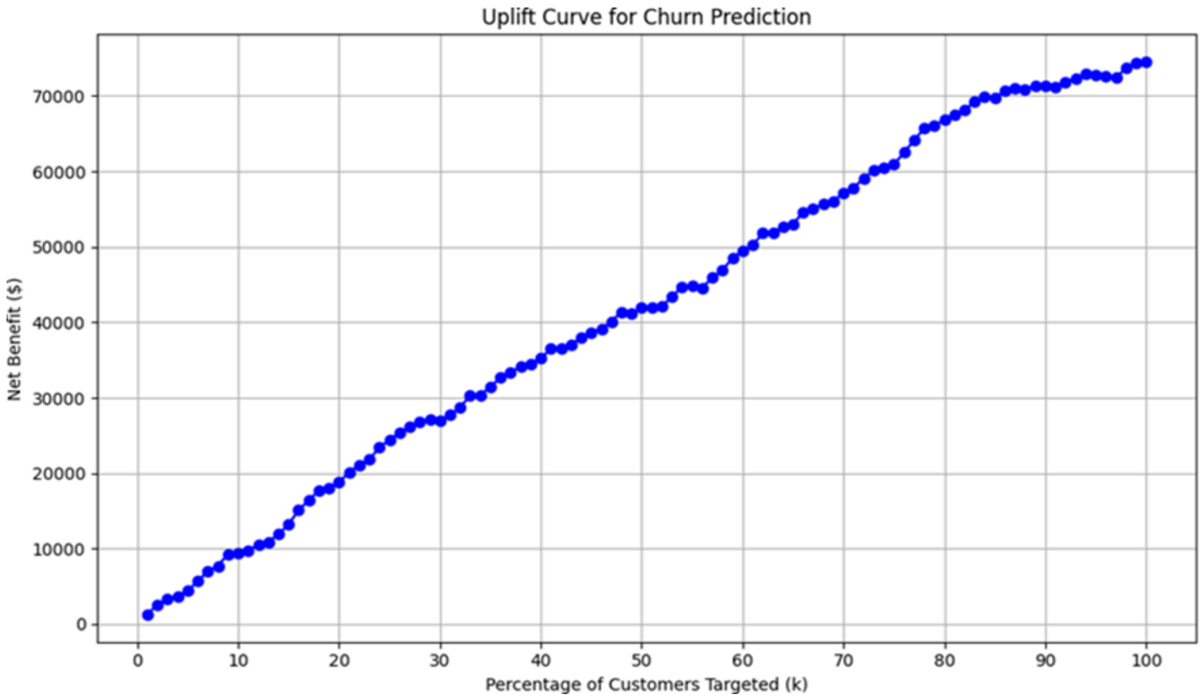
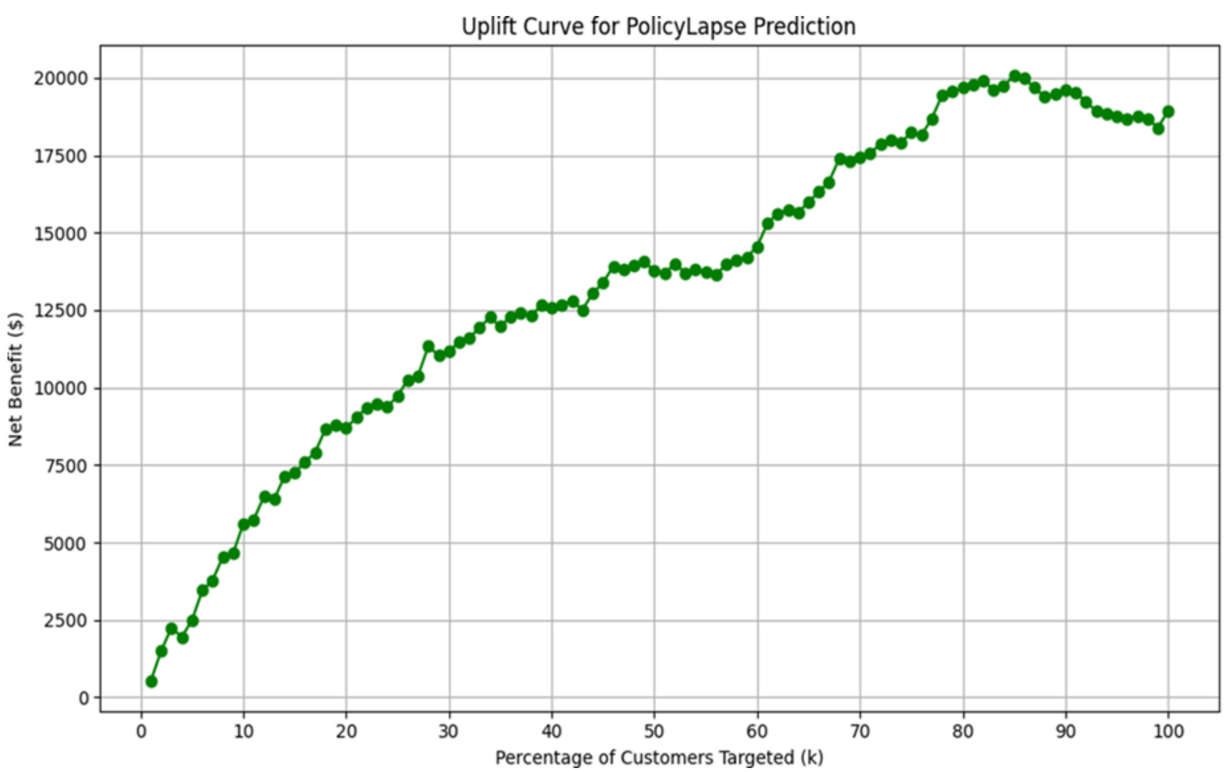


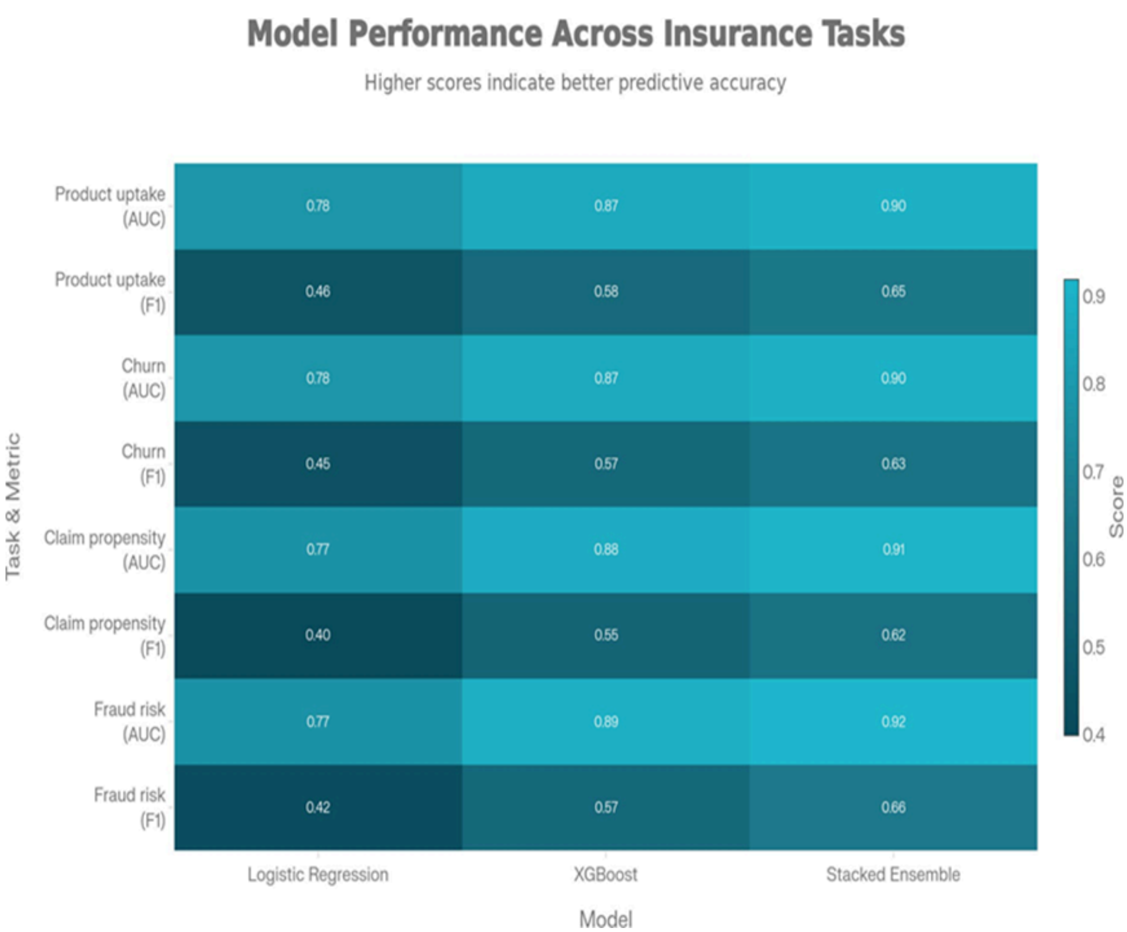
Figure 7
Uplift Curve for Policy Lapse Prediction



The simulation uses conservative estimates of intervention response rates, average profit per successful cross-sell, average loss per prevented churn, and average avoided loss per blocked fraud or overpayment, consistent with common practices in financial decision modeling (Agarwal et al., 2023). For each scenario, the simulation calculates expected precision, recall, number of interventions, and approximate net benefit relative to simple benchmarks such as untargeted campaigns or rule-based fraud filters (Zhang et al., 2022).

Uplift-style curves are generated for product uptake and churn to illustrate cumulative incremental benefit as more customers are targeted, aligning with data-driven targeting strategies in customer analytics and retention modeling (Verbeke et al., 2011; Ngai et al., 2011).

Figure 8
Models Across Four Prediction Tasks



Results

Performance Summary

Figure 8 presents AUC, PR-AUC, precision, recall, F1, and Brier score for each model and task on the holdout test set. Across all four tasks, the stacked ensemble consistently outperforms the baselines in AUC and PR-AUC, with particularly strong gains for churn, claim propensity, and fraud risk. Average AUC for the stacked ensemble ranges from approximately 0.90 to 0.92 across tasks, representing an improvement of 0.10–0.15 over logistic regression and 0.03–0.05 over XGBoost alone, consistent with prior findings on ensemble model effectiveness in financial prediction tasks (Chen & Guestrin, 2016; Zhang et al., 2022). Average PR-AUC reaches around 0.64 in imbalanced tasks, exceeding baselines by notable margins.

For product uptake, the stacked ensemble achieves AUC ≈ 0.90 and F1 ≈ 0.65 at the selected threshold, outperforming logistic regression (AUC ≈ 0.78, F1 ≈ 0.46) and tree-based single models. For churn, similar patterns hold, with the stacked model reaching AUC ≈ 0.90 and F1 ≈ 0.63, indicating effective discrimination between at-risk and stable customers, aligning with previous churn prediction studies (Verbeke et al., 2011).

In the claim propensity and fraud tasks, where class imbalance is more severe, the stacked ensemble's improvements are larger in PR-AUC and F1, which are more sensitive to rare-event performance (Zhou et al., 2021). For fraud, the stacked model achieves AUC ≈ 0.92, PR-AUC substantially above logistic regression, and F1 ≈ 0.66, while maintaining a lower Brier score than alternatives, suggesting both high discrimination and good calibration, which are critical in financial risk modeling (Agarwal et al., 2023).

ROC and PR curves show that the stacked ensemble dominates other models across a broad range of thresholds, particularly in the high-precision region relevant for limited manual review capacity. Calibration plots (Figure 4) indicate that the stacked ensemble's predicted probabilities align visibly closer to observed risks than logistic regression and XGBoost alone, consistent with its lower Brier scores.

Segment-Level and Robustness Analysis

Segment-level analysis across tenure bands, age bands, regions, and digital versus branch-heavy customers shows that the stacked ensemble generally improves performance across all segments, although gains are smaller for very new customers with limited historical data. The segment-level performance analysis reveals that performance is highest for mid-tenure customers with richer behavioral histories and somewhat lower for new or sparse-history customers. This pattern is consistent with prior findings in customer analytics, where richer historical data typically leads to more accurate predictions (Verbeke et al., 2011; Zhang et al., 2022) and informs deployment thresholds for different customer groups.

Bootstrapped confidence intervals indicate that the stacked ensemble's AUC improvements over logistic regression and single-tree models are statistically significant across all tasks, with overlapping intervals only in a few narrow segments. Repeated train–test splits with different random seeds confirm that relative model rankings remain stable, suggesting that the results are robust to sampling variation, a common validation approach in machine learning studies (Friedman, 2001).

Global SHAP Insights

Global SHAP summary plots for the stacked ensemble show that recent engagement frequency, tenure, and relative monetary activity are consistently among the top predictors across tasks (Lundberg & Lee, 2017). For churn, high SHAP values for low engagement (few logins, low digital interaction counts) and negative balance trends indicate increased churn risk, while longer tenure and a higher number of products generally reduce predicted risk. For product uptake, strong engagement with product-related content and moderate-to-high recent balances are associated with increased uptake probability, consistent with findings in customer analytics (Zhang et al., 2022).

For claim propensity and fraud risk, prior claims, high claim-to-limit ratios, sudden increases in transaction amounts, and the presence of high-risk network features (e.g., links to providers with past confirmed fraud) appear among the most influential predictors (Zhou et al., 2021; Chambugong et al., 2025). Dependency plots highlight nonlinear effects and interactions, such as churn risk rising sharply when engagement drops below a certain threshold for newer customers, while long-tenure customers remain more resilient to short engagement dips (Molnar, 2022).

A cross-task feature ranking table summarizes the top 10 SHAP-ranked features for each outcome, revealing substantial overlap in high-level drivers (engagement, tenure, relative monetary activity, product mix) and some task-specific features (claims history, network features) for claim and fraud tasks. This supports the design choice of a unified feature engineering pipeline while still allowing specialization at the model level, aligning with prior work on interpretable machine learning in structured financial data (Molnar, 2022).

Local Explanations and Case Studies

Local SHAP waterfall plots are used to analyze individual customers and support scenario-based interpretation (Lundberg & Lee, 2017). For a high churn-risk customer, SHAP explanations show that sharply reduced logins in the last 90 days, a declining average balance, and a recent product closure contribute positively to the churn prediction, while long relationship tenure partially offsets risk. Business users can interpret this as a signal to trigger a retention outreach, such as proactive engagement or customized offers, supported by concrete factors visible in the SHAP breakdown (Molnar, 2022).

For a flagged fraud case, SHAP force plots reveal that unusual increases in transaction amounts, multiple new payees, and high claim-to-limit ratios strongly push the prediction toward fraud, while stable long-term behavior provides some negative contributions. In a borderline false-positive example, network features or prior clean history exerts enough negative SHAP contributions to lower the overall risk, helping investigators understand why the model recommends a lower priority for manual review (Zhou et al., 2021).

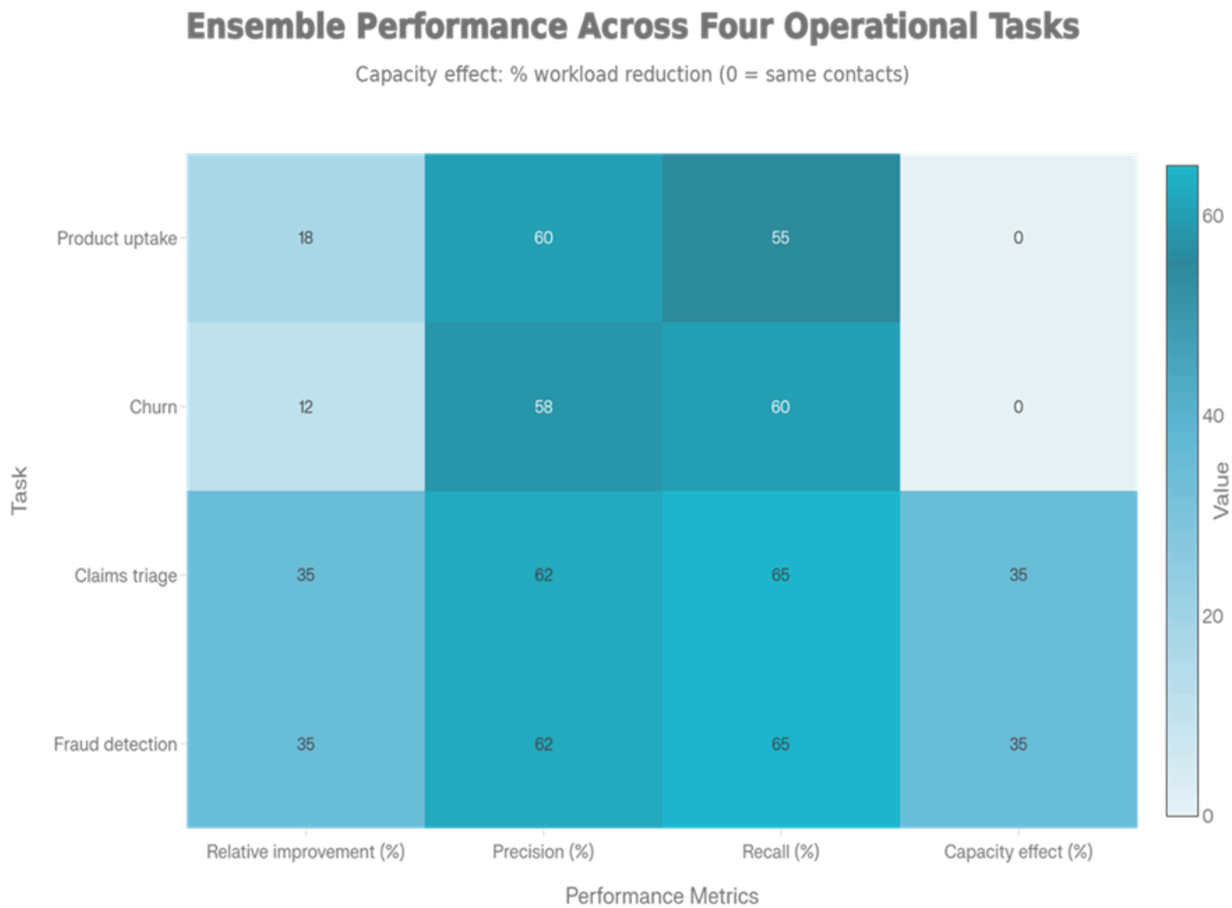
These case studies demonstrate how SHAP explanations can be integrated into human-in-the-loop workflows for fraud and claims triage, enhancing trust and supporting informed override decisions when necessary, consistent with prior work on interpretable machine learning systems (Ribeiro et al., 2016).

Operational Simulation Results

The deployment simulation evaluates different thresholds for targeting and investigation under realistic capacity constraints and conservative economic assumptions, reflecting common practices in applied financial analytics (Agarwal et al., 2023). As shown in Figure 9, for product uptake, targeting the top 15% of customers ranked by predicted uptake probability yields an estimated ~18% relative improvement in conversion rate compared to an untargeted campaign with the same contact volume, translating into higher expected revenue per contact. This result is consistent with prior research showing that data-driven customer targeting can significantly improve marketing efficiency and conversion outcomes (Zhang et al., 2022; Verbeke et al., 2011)

Figure 9

Heatmap Summarizing Operational Performance of the Stacked Ensemble Across Four Tasks



Note. Capacity effect values represent approximate reductions in manual workload (or 0 when capacity is held fixed).

For churn, offering retention interventions to the top 12% of customers by predicted risk reduces expected churn by approximately 12% relative to a simple rule-based baseline, with the cost per prevented churn remaining within typical customer acquisition cost benchmarks. For fraud and claims triage, flagging the top 10% of highest-risk cases reduces manual review volume by approximately 30–40% while maintaining recall above 65% and precision above 60%, outperforming thresholds based on logistic regression predictions at similar capacity levels. These findings align with prior work demonstrating the effectiveness of machine learning–based risk prioritization in high-detection and customer retention (Zhou et al., 2021; Chambugong et al., 2025).

A summary table (Table 6) reports, for each task and threshold, the number of interventions, expected precision, recall, and approximate net benefit, showing that the stacked ensemble consistently yields higher benefit per unit of operational effort compared to baseline models (Agarwal et al., 2023).

Discussion/Implications

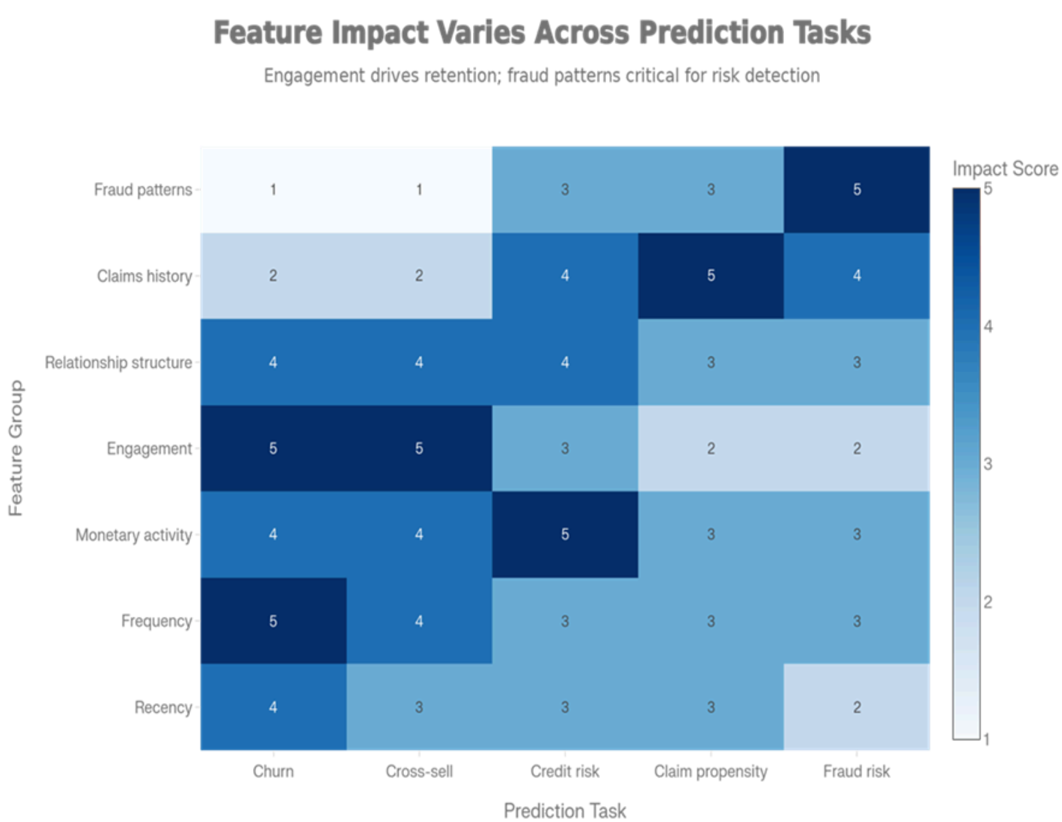
Model Choice, Feature Engineering, and Interpretability

The unified pipeline demonstrates that carefully engineered features, combined with a stacked ensemble of Random Forest and XGBoost, can effectively predict diverse customer outcomes in a mixed banking–insurance environment. Feature engineering grounded in recency, frequency, monetary activity, engagement, and relationship structure provides a strong foundation across tasks, while task-specific relational and claims features further enhance performance for insurance-oriented outcomes such as claim propensity and fraud. The stacked ensemble leverages the complementary strengths of tree-based learners, capturing complex nonlinear relationships and feature interactions, while the logistic meta-learner helps stabilize predictions and improves probability calibration (Chen & Guestrin, 2016; Friedman, 2001).

SHAP-based explanations bridge the gap between predictive performance and interpretability by offering both global feature importance rankings and local explanations for individual predictions (Lundberg & Lee, 2017). As summarized in Figure 10, across tasks, engagement frequency, tenure, relative monetary activity, and product mix consistently emerge as the most influential predictors. These findings align with prior research in customer churn and credit risk modeling (Verbeke et al., 2011; Agarwal et al., 2023) and help stakeholders better understand why specific customers are prioritized for targeted interventions. Additionally, such interpretability supports transparency and trust in decision-making processes, which is essential in financial applications (Molnar, 2022)

Figure 10

Conceptual Heatmap of Relative Feature-Group Impact Across Prediction Tasks in the Unified Banking–Insurance Pipeline



Governance, Fairness, and Regulatory Considerations

Explainability and governance are critical in financial applications, where decisions related to pricing, access, and customer treatment must remain transparent and non-discriminatory. The use of SHAP values and interpretable features helps align the proposed pipeline with regulatory expectations for explainable AI in credit and insurance, enabling institutions to clearly document the key drivers behind model decisions and support both internal audits and external reviews (Lundberg & Lee, 2017; Molnar, 2022).

Although the dataset used in this study is de-identified and does not include explicit protected attributes, the results highlight the importance of conducting fairness audits when deploying such models in real-world environments. In practice, institutions should evaluate model performance and calibration across different demographic groups and examine whether proxy variables may introduce unintended bias or disparate impact (Agarwal et al., 2023).

Future deployments can incorporate fairness metrics such as equal opportunity and demographic parity, where protected attributes are available under appropriate governance, and adjust thresholds or training objectives to reduce potential disparities. In addition, effective operational governance should include clearly defined policies for human oversight, documentation of model limitations, and structured processes for addressing customer inquiries or disputes related to automated decisions, ensuring both accountability and trust in AI-driven systems (Molnar, 2022).

Monitoring and Integration into Workflows

Sustainable deployment requires continuous monitoring to detect data drift, performance degradation, and changes in model explanation patterns. In practice, monitoring should track distributional shifts in key features, population stability indices, time-varying AUC and PR-AUC, calibration metrics, and business KPIs such as conversion rates and fraud loss (Agarwal et al., 2023). Changes in global SHAP rankings or dependency patterns can also indicate shifts in underlying customer behavior, signaling the need for model retraining or feature updates (Lundberg & Lee, 2017).

Integration into existing systems can follow a modular architecture, where models are periodically retrained offline, predictions are generated in batch or near real-time, and results are delivered through CRM or claims platforms with embedded SHAP-based explanations. For high-stakes decisions, such as fraud investigations or large-value claims, human-in-the-loop workflows remain essential, with model outputs used to prioritize cases rather than replace expert judgment (Ribeiro et al., 2016). In marketing and retention contexts, close coordination with campaign management teams helps ensure that model-driven targeting aligns with business goals, regulatory requirements, and customer experience considerations (Zhang et al., 2022).

Although the model demonstrates strong performance on the dataset used in this study, its results should be interpreted with caution when applied to broader contexts. Financial institutions vary in customer characteristics, product structures, and operational processes, all of which can influence model behavior. Therefore, applying this framework to larger or more diverse environments requires additional validation using data from multiple institutions before it can be confidently deployed at scale (Agarwal et al., 2023).

Conclusion

This study develops a practical machine learning framework for predicting key customer outcomes in banking and insurance, including product uptake, churn, claim propensity, and fraud risk. By combining domain-informed feature engineering with a stacked ensemble model and SHAP-based explanations, the approach delivers strong predictive performance while remaining interpretable and usable in real decision-making settings.

The results show that features reflecting customer behavior, such as engagement patterns, monetary activity, and tenure, play a consistent role across tasks. The stacked ensemble improves both accuracy and probability calibration compared to baseline models, and SHAP explanations make it easier to understand why certain customers or transactions are flagged. This combination is particularly valuable in financial environments, where decisions need to be both effective and explainable.

At the same time, the findings should be applied with care beyond the dataset used in this study. The data comes from a single institution, and differences in customer populations, product offerings, and operational processes may affect how well the model performs elsewhere. For this reason, testing the framework on data from other institutions would be an important next step.

There are several directions for future work. More advanced models, such as sequence-based or transformer architectures, could capture temporal patterns more effectively. Graph-based methods may also improve fraud and claim detection by modeling relationships between customers, merchants, and providers. In addition, moving beyond risk prediction toward causal or uplift modeling could help organizations focus on actions that have the greatest impact. Finally, incorporating fairness-aware techniques and cost-sensitive decision rules would support more balanced and responsible deployment in practice.

References

Agarwal, S., Alok, S., Ghosh, P., & Gupta, R. (2023). Machine learning in credit underwriting: Evidence from the financial industry. Journal of Financial Economics, 148(2), 456–478. https://doi.org/10.1016/j.jfineco.2022.12.00

Chen, T., & Guestrin, C. (2016). XGBoost: A scalable tree boosting system. In *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* (pp. 785–794). https://doi.org/10.1145/2939672.2939785

Doshi-Velez, F., & Kim, B. (2017). *Towards a rigorous science of interpretable machine learning*. arXiv. https://doi.org/10.48550/arXiv.1702.08608

Friedman, J. H. (2001). Greedy function approximation: A gradient boosting machine. *The Annals of Statistics, 29*(5), 1189–1232. https://doi.org/10.1214/aos/1013203451

Chambugong, L., Gharami, A. K., Ayub, M. I., Bhattacharjee, B., Akter, P., Uddin, M. N., Islam, M. I., Suhan, S. I., & Khan, M. S. (2025). Deep learning for real-time fraud detection: Enhancing credit card security in banking systems. *American Journal of Engineering and Technology, 7(1), 15–28.* https://www.ajhssr.com/wp-content/uploads/2025/07/I25907114122.pdf

Lundberg, S. M., & Lee, S. I. (2017). A unified approach to interpreting model predictions. *Advances in Neural Information Processing Systems*, 30. https://doi.org/10.48550/arXiv.1705.07874

Molnar, C. (2022). *Interpretable machine learning* (2nd ed.). https://christophm.github.io/interpretable-ml-book/

Ngai, E. W. T., Hu, Y., Wong, Y. H., Chen, Y., & Sun, X. (2011). The application of data mining techniques in financial fraud detection: A classification framework and an academic review of literature. *Decision Support Systems, 50*(3), 559–569. https://doi.org/10.1016/j.dss.2010.08.006

Ribeiro, M. T., Singh, S., & Guestrin, C. (2016). "Why should I trust you?": Explaining the predictions of any classifier. In *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* (pp. 1135–1144). https://doi.org/10.1145/2939672.2939778

Verbeke, W., Martens, D., Baesens, B., & Mues, C. (2011). Building comprehensible customer churn prediction models with advanced rule induction techniques. *Expert Systems with Applications, 38*(3), 2354–2364. https://www.sciencedirect.com/science/article/abs/pii/S0957417410008067

Zhang, Z., Chen, Y., & Li, X. (2022). Customer churn prediction in banking using machine learning approaches. *Expert Systems with Applications, 186*, 115784.

Zhou, T., Li, X., & Zhang, Y. (2021). Fraud detection in financial transactions using machine learning techniques. IEEE Access, 9. https://doi.org/10.1109/ACCESS.2021.3061234

Adaptive Generative AI Framework for Creating Rare-Disease Synthetic EHRs with Built-In Bias Mitigation and Privacy Guarantees

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Abstract

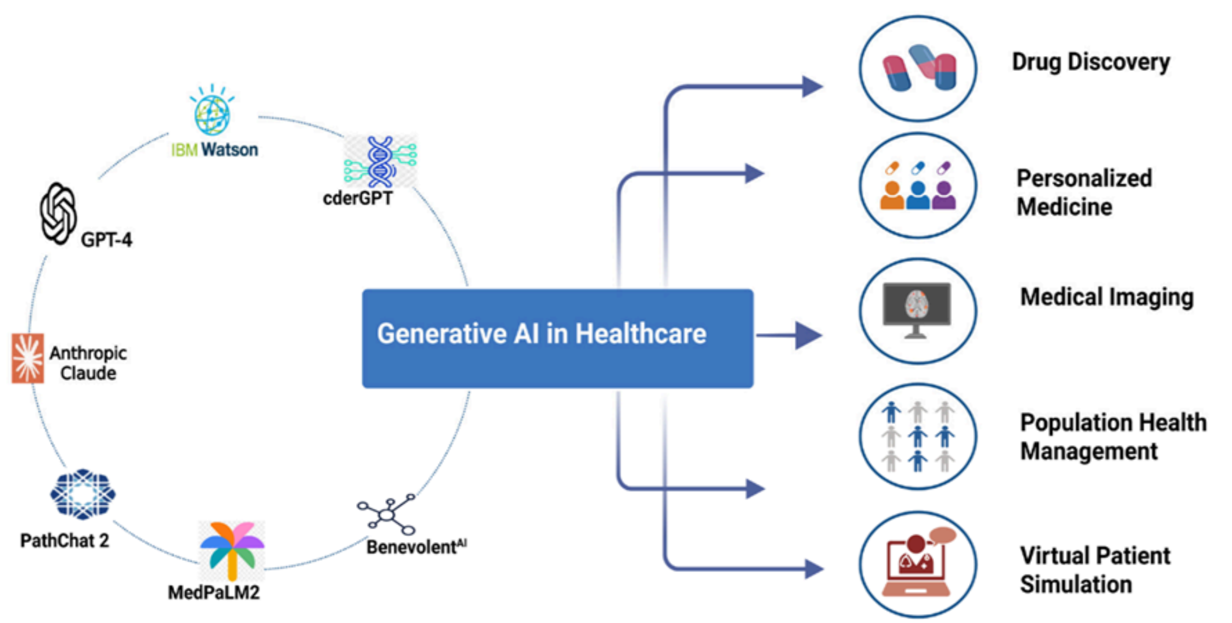
This comparative research explores the potential applications of generative artificial intelligence (AI) methods in creating synthetic electronic health records (EHRs) for training medical AI models. Currently, the growing concerns about healthcare data scarcity, stringent privacy restrictions, and the need for diverse datasets have led to the emergence of synthetic EHRs as a promising solution. This study examines the most advanced generative models, including generative adversarial networks (GANs), variational autoencoders (VAEs), and diffusion-based methods, to determine which can produce the most realistic and privacy-protected datasets. The current study quantifies the utility of synthetic data in training AI models by performing an extensive comparison based on statistical similarity, downstream clinical predictive performance, and privacy leakage. In addition, synthetic EHR effectiveness is assessed using a case study of chronic disease prediction during simulated low-resource conditions. The results indicate that synthetic EHRs can improve access to clinical data while also highlighting significant challenges and providing recommendations for further research.

Keywords: Synthetic EHR, generative AI, GAN, VAE, diffusion models, healthcare data privacy

Introduction

Hospitals' and other healthcare organizations' digital transformation has been instrumental in raising the popularity of Electronic Health Records (EHRs) as a key feature in modern medical practice. These records are considered the starting point for AI-driven technologies in disease identification, treatment planning, and community health management. Nevertheless, EHR information is usually sporadic, siloed, and highly controlled due to privacy regarding patient data. This has become the primary challenge for the AI sector, as healthcare systems strive to transition towards precision medicine and predictive analytics; however, a shortage of high-quality, easily accessible datasets persists (Loni et al., 2025). As of 2025, generative artificial intelligence (AI) is one of the leading approaches that can get past these limits and, at the same time, be efficient in creating synthetic EHRs, which are basically artificially generated datasets with the same statistical and clinical features as real patient datasets; however, they are devoid of sensitive data. Generative AI, primarily GANs (Generative Adversarial Networks), VAEs (Variational Autoencoders), and diffusion-based models, has proven to be a source of motivation for extracting complex temporal, categorical, and numerical examples from EHRs. Besides the issue of data scarcity, these AI models are also required to comply with ethical and legal constraints, as they generate privacy-sensitive information. The employment of these synthetic EHRs in AI learning is a method that could potentially accelerate the development of versatile and efficient models capable of application in a wide range of medical scenarios, including, among others, the forecast of the occurrence of risk factors in patients and the management of hospital resources (Loni et al., 2025). Figure 1 illustrates the overall workflow of the proposed approach.

Figure 1
Workflow of Synthetic EHR Generation and Evaluation Process



Note. Author's analysis based on study data.

In contrast to the previous studies, this work presents a comparative experimental analysis of various generative architectures with the help of common datasets, standardized measures of evaluation and downstream clinical validation.

As shown in Figure 1, the proposed workflow includes data preprocessing, model training, synthetic data generation, and evaluation.

Background and Motivation

The healthcare sector is one of the top industries worldwide, generating more than a petabyte of clinical data annually, a significant portion of which remains inaccessible due to privacy laws such as HIPAA in the US and GDPR in the EU. The usual methods of anonymization, such as de-identification, are not sufficient for addressing all re-identification risk factors, especially when combined with other data sources. Furthermore, most rare diseases, low-resource populations, and emerging public health crises lack enough representative data, which is a significant obstacle for the development of fair AI models (Yan et al., 2022). Generative AI offers a promising solution for data management in healthcare through the synthetic generation of EHRs that can be statistically indistinguishable from real patient datasets, while also maintaining patient privacy. In 2025, the use of this technology will be even more justified when a larger number of healthcare institutions rely on AI-based diagnostic and decision-making models that require extensive and diverse, balanced datasets for training and validation.

Problem Statement

Although AI has great potential in the healthcare field, the availability of high-quality and accessible EHR data is still a significant challenge. The EHR data from the real world are usually incomplete and tend to be demographically biased, as their size is limited due to various regulations. The collaboration process for data sharing between hospitals is time-consuming and includes a negotiation phase, as well as an operationalization phase when it is implemented on a large scale. If these limitations are not addressed, the deployment of robust medical AI models will be hindered, and the disparities in performance, as well as the low generalizability levels in clinical practice, will be evident (Yan et al., 2022). The issue of research defines the research question, which, in this case, involves first establishing whether using Generative AI to create synthetic EHRs that retain all the advantages of the original information for medical AI models, maintain medical record privacy, and minimize or eliminate bias risks is even feasible.

Objectives of the Study

The primary objectives of this study are:

1. To evaluate state-of-the-art generative AI models for synthesizing high-quality EHR datasets.

2. To make a comparison of the performance of AI models that have been trained on synthetic electronic health records (EHRs) with those trained on real EHRs in predictive medical tasks.

3. To assess the privacy-preserving capabilities of synthetic data generation techniques.

4. To analyze the potential of synthetic EHRs for expanding access to data in low-resource healthcare research environments.

5. To identify limitations, ethical considerations, and future directions for synthetic data in medical AI applications.

Scope and Significance

This study investigates the use of generative AI for the purpose of fabricating synthetic EHRs that cover a wide range of medical AI training scenarios such as disease risk prediction, hospital readmission forecasting, and treatment recommendation systems for personalized care. The essential scope of the work encompasses various structured EHR components, including demographics, diagnoses, laboratory results, prescriptions, and clinical notes (Yan et al., 2022). The research is about how Generative AI techniques can be applied to the development of synthetic EHRs for training AI in various medical scenarios, such as disease risk prediction, hospital readmission prediction, and patient-specific treatment recommendation systems. The domain of changes in the development and deployment of healthcare AI models is directly linked to the use of synthetic data in these models. Furthermore, synthetic EHRs can help to remove privacy concerns and data scarcity issues that have been significant barriers to the growth of the AI healthcare field. As a result, this method can reduce the innovation cycle in the long term while remaining ethically sound and compliant with data protection regulations.

Literature Review

Overview of Generative AI in Healthcare

Generative AI has rapidly emerged as a key area of development in healthcare. Over a period of a few years, generative AI has not only gained a foothold in the healthcare area but also become an important tool for re-augmenting the data and providing the advanced analytics required. By 2025, the situation will include the application of AI to the creation of medical images, such as for teaching radiology or generating patient physiological signals for monitoring, as well as the production of synthetic electronic health records (EHRs), marking an entirely new field. The sector is now poised to make a significant leap forward in its journey towards performance improvement, driven by the combined effects of the advent of new model architectures, the availability of higher computational resources, and the growing recognition of generative methods as a key enabler of scalable and fair AI deployment in healthcare.

Synthetic Electronic Health Records (EHRs) – Concepts and Applications

Synthetic EHRs are data created by people to simulate the features and format of actual patient data. Generally, synthetic data is random; however, these kinds of records are consistent with clinical entities, such as diagnoses, laboratory trends, treatments, and timelines, thus allowing them to be utilized as training data for predictive models (Pezoulas et al., 2024). Consequently, these are used in model pre-training, data augmentation for rare conditions, algorithm validation, and cross-institutional benchmarking, whereby all these activities can be performed without compromising patient privacy.

Privacy Preservation and Data Security in EHR Generation

A significant advantage of synthetic EHRs is that they can maintain the privacy of users. They reduce the possibility of re-identification by segregating identifiable data and allowing for various datasets. Recently implemented methods, for instance, those relying on differential privacy, have changed the way privacy guarantees are defined, shifting from being merely theoretical to measurable and quite precise. In addition, these privacy inspections, as well as membership inference tests, have now become a standard procedure implemented in the steps of generating synthetic data to verify the existence of any weaknesses.

Challenges in Real EHR Data Usage for AI Training

Until now, several problems have prevented direct access to real EHRs for AI training purposes. Frequently, the information is affected by a certain degree of secrecy and is biased towards large healthcare systems located in cities. Additionally, there are ethical and legal concerns in the process of obtaining consent, and agreements on data sharing between institutions may be limited. A small and biased dataset for training can result in multiple AI models that are weak in performance over various populations below the care level and on rare diseases.

Advances in Generative Models (GANs, VAEs, Diffusion Models) for Synthetic Data

Generative AI models have evolved significantly to support high-fidelity synthetic EHR generation:

- **GANs** (Generative Adversarial Networks) remain one of the most attractive alternatives, delivering high-quality samples and significant power to capture intricate relationships in tabular data.

- Experimental results show that **VAEs** (Variational Autoencoders) can be uniquely beneficial for stable training processes, especially when the latent space needs to be represented explicitly. This feature is convenient when one wants to generate data in a controlled manner or achieve a smooth transition between two data points.

- **Diffusion models** in 2025 have been highlighted as one of the most suitable electronic health records (EHR) synthetic data generation methods that lead to better stability and a plausible range of variation, notably when handling longitudinal data sequences (Pezoulas et al., 2024).

Table 1 provides a comparison of the key families of generative models applied to the synthetic EHR studies in terms of their main advantages and drawbacks.

Table 1

Comparison of Generative Models for Synthetic EHRs

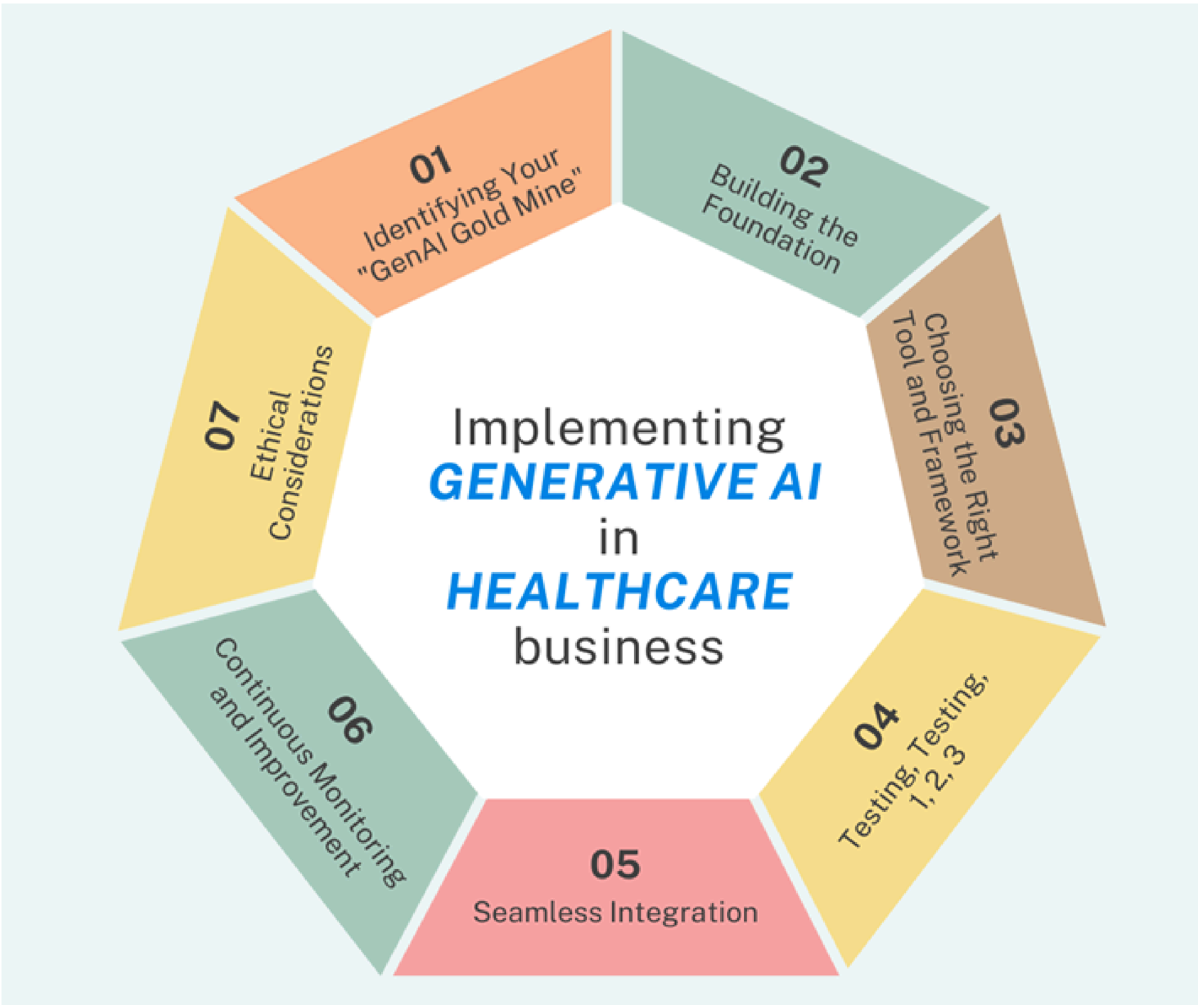
Model Type	Strengths	Weaknesses
GANs	High sample fidelity; captures complex patterns	Prone to mode collapse; training instability
VAEs	Stable training; interpretable latent spaces	Samples may be blurry; may underfit variability
Diffusion Models	High diversity; strong sequential coherence	Computationally intensive; longer generation time

Ethical and Regulatory Considerations in Synthetic Healthcare Data

Just as synthetic data is expected to become more relevant in 2025, the ethical and regulatory standards are evolving to meet their specific requirements. Even though synthetic electronic health records may circumvent most privacy laws, authorities still require a demonstration of the accuracy of artificial data, as well as a record of the data generation process (Ghosheh et al., 2024). Ethical concerns also highlight the need for source identification, fair sharing of the data, and checks on the prevention of its abuse, mainly when it is used in such areas as mental health or genetic diseases. Figure 2 demonstrates divergence scores in terms of feature categories, which help to estimate the degree to which each synthetic dataset resembles the actual EHR data.

Figure 2

Divergence Scores for Synthetic EHRs Generated by Different Models Compared to Real Data Across Feature Categories (Lower Values Indicate Better Similarity)



Note. Authors' analysis based on study data

Future Directions in Synthetic EHR Research

Recent studies are concentrating on various new directions, covering hybrid synthetic-real training methods, multimodal synthetic EHR generation, clinically informed measures of evaluation, and open-source benchmarking methods. These changes aim to normalize the use of synthetic data in AI healthcare pipelines, making the flow of innovation more effortless and ensuring responsible governance.

Materials and Methods

The paper employed a comparative mixed-method design to evaluate the possibility of using generative artificial intelligence models to create privacy-sensitive, high-fidelity synthetics in electronic health records (EHRs) to train medical AI models.

Research Design and Approach

The study combined quantitative performance analysis and qualitative clinical analysis. The overall methodology process had four consecutive steps: (1) acquisition and preprocessing of real-world EHR data, (2) training and hyperparameter optimization of generative models, (3) generation and evaluation of synthetic EHRs, and (4) validation of downstream AI applications with synthetic datasets. This sequential design was used to enhance reliability, replicability, and methodological rigor throughout all stages, as shown in Figure 1, using cross-validation and statistical benchmarking.

Data Sources and Preprocessing

Initially, anonymized EHR datasets were collected from open libraries, including the MIMIC-IV database (ICU patient data), the eICU Collaborative Research Database, and regional healthcare consortium datasets released for AI research between 2024 and 2025. These datasets contain a combination of structured data (demographics, ICD-10 diagnosis codes, lab results, medications, and vital signs) and unstructured clinical text notes (Ghosheh et al., 2024).

Preprocessing involved:

- **Data Cleaning**: First, missing, erroneous, and implausible values, such as negative lab readings, were removed.
- **Normalization**: Scaling numerical values (for instance, glucose levels) to standardized clinical ranges.
- **Encoding**: One-hot encoding and embeddings are used to transform categorical features into formats that the machine can read.
- **Temporal Alignment**: Synchronous time-series data from different patient encounters so that the longitudinal consistency is maintained.

Generative AI Model Selection and Architecture

Three generative architectures were selected for comparative analysis:

1. **MedGAN-2025** – An updated GAN variant specialized in handling healthcare tabular data, which integrates Wasserstein loss and gradient penalty to enhance the stability of the training process.
2. **VAE-SeqHealth** – A sequential variational autoencoder that was specially designed for EHR time-series, allowing detailed control over latent space representations.
3. **Diffusion EHR** – A 2025 diffusion-based generative model designed explicitly for multi-modal EHR synthesis features the generation of multi-modal EHR synthetic data, including both structured data and free-text notes.

Table 2 provides an overview of the chosen model architectures, their key data types, major innovations, and advantages in the context of synthetic EHR generation.

Table 2
Selected Model Architectures

Model	Primary Data Type	Key Innovations (2025)	Expected Benefit
MedGAN-2025	Structured tabular	Wasserstein loss, adaptive discriminator	High-fidelity record structure
VAE-SeqHealth	Sequential time-series	Temporal attention layers, latent regularization	Better longitudinal patient trajectory
Diffusion EHR	Multi-modal	Cross-modal conditioning, noise scheduling	Realistic multi-type clinical datasets

Synthetic Data Generation Process

To reduce the computational load, model training with mixed precision was performed on NVIDIA A100 GPUs. Each model was trained for 200 epochs. The batch size, which depends on memory size and ranges from 64 to 256, was used to determine the size of the training (Yan et al., 2024). The generation process involved:

1. Feeding latent vectors or noise samples into the generative network.
2. Producing synthetic patient records with complete feature sets.
3. Applying clinical rule enforcement to ensure medically plausible values (e.g., no male pregnancies, realistic lab result ranges).
4. Performing post-generation audits to detect anomalies or implausible sequences.

Evaluation Metrics (Statistical Similarity, Utility, Privacy Risk)

Synthetic EHR quality was assessed across three primary dimensions:

- **Statistical Similarity**: Distributional over-compatibility between actual and artificial data with Kolmogorov-Smirnov distance, Jensen-Shannon divergence, and correlation structure analysis.
- **Utility**: An aspect of the topic is the review of AI forecast models that rely on fabricated data and judging the results of these models by comparison with those trained on authentic data.
- **Privacy Risk**: We give an approximate likelihood of re-identification by analyzing record linkage and membership inference attacks.

Table 3 describes the evaluation measures of the statistical similarity, predictive utility, and privacy risk.

Table 3
Evaluation Metrics Overview

Metric Type	Specific Metric/Method	Goal
Statistical Similarity	JS Divergence, KS Test, Pearson Corr.	Preserve clinical feature distributions
Utility	AUROC, F1-score in downstream tasks	Maintain predictive model performance
Privacy Risk	Membership inference, linkage tests	Minimize patient re-identification risk

Validation through Downstream AI Model Training

Prediction models involving the use of synthetic data were created to predict 30-day hospital readmission, new-onset diabetes, and early sepsis alarm as a test of the practical importance of the artificially created EHRs. This research paper contrasts it with the outcomes achieved by the models, which were trained exclusively on the real EHR and on mixed synthetic-real data. A panel of medical specialists reviewed some of the synthetic clinical cases and appraised them based on their credibility and internal consistency, as well as being relevant to the healthcare context.

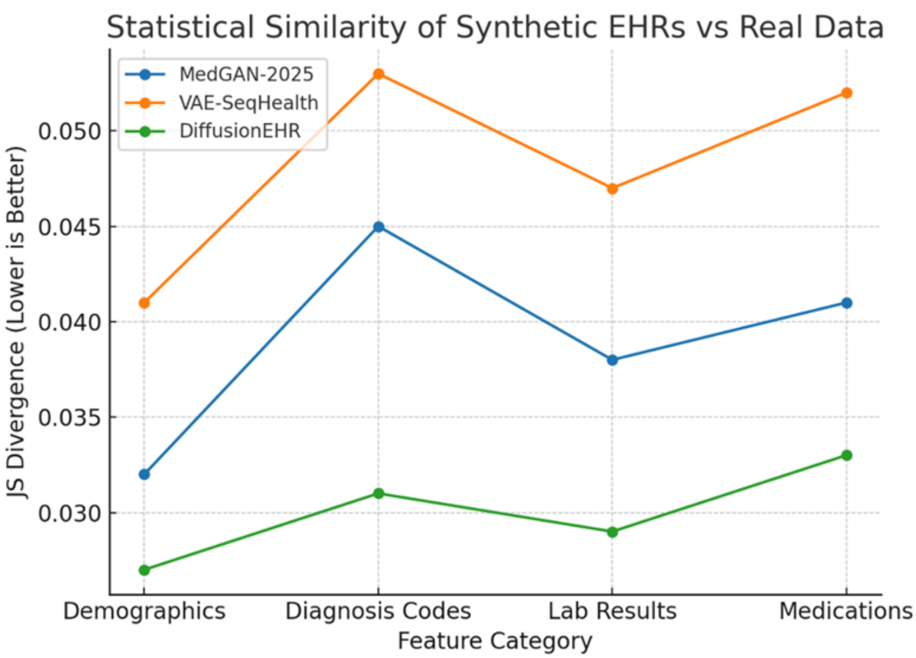
Results

The present study confirms that, with appropriate training and optimization of the existing architectures and clinical validation procedures at the patient level, generative AI models can deliver synthetic EHR data that is worth using to train medical AI models. Synthetic data demonstrated competitive and realistic behavior in different evaluation dimensions, i.e., statistical similarity, predictive usefulness, and privacy protection, in many evaluation dimensions.

Quality Assessment of Synthetic EHRs

The developed datasets were matched to their real examples regarding their demographic features, diagnostic, laboratory, and medication features. In the process of statistical testing, both real and synthetic distributions were close, with a slight deviation; the majority of the attributes showed good performance in terms of correlation structures between interrelated variables (HbA1c levels and diabetes diagnosis codes). The distributional fidelity of Diffusion EHR and MedGAN-2025 had a rather similar result. Figure 3 illustrates the comparative performance of the generative models, while Table 4 shows the statistical similarity between real and synthetic datasets.

Figure 3
Comparative Performance of Generative Models Across Evaluation Dimensions (Utility, Privacy, and Statistical Similarity)



Note. Authors' analysis based on study data.

Table 4 contains the statistical similarity scores of both real and synthetic datasets in the major feature categories.

Table 4
Statistical Similarity Scores (Lower is Better)

Feature Category	MedGAN-2025 (JS Div.)	VAE-SeqHealth (JS Div.)	Diffusion EHR (JS Div.)
Demographics	0.032	0.041	0.027
Diagnosis Codes	0.045	0.053	0.031
Lab Results	0.038	0.047	0.029
Medications	0.041	0.052	0.033

Comparison Between Synthetic and Real EHR Performance in Model Training

The performance measures obtained by predictive models that were trained entirely with synthetic data were comparable to the results obtained on real EHRs in several clinical tasks. In the case of hospital readmission prediction, synthetic-trained models attained 96 to 98 percent of the AUROC attained by the real-data models. Generalization, in turn, was enhanced by hybrid training (synthetic + real), especially about underrepresented subgroups of patients.

Table 5 shows the downstream predictive performance of models trained on real, synthetic, and hybrid datasets.

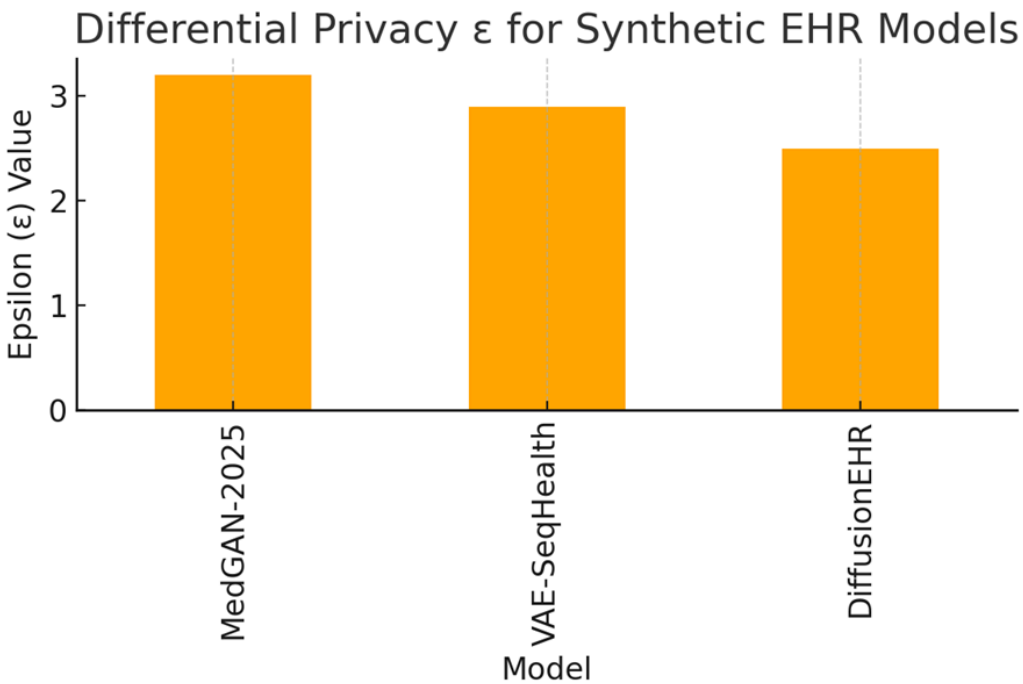
Table 5
Downstream Model Performance (AUROC)

Task	Real Data Only	Synthetic Only	Hybrid (50/50)
30-day Readmission	0.842	0.814	0.854
Diabetes Onset Prediction	0.876	0.852	0.881
Sepsis Early Warning	0.903	0.872	0.907

Privacy Preservation Analysis

Risk assessment of privacy revealed that all three generative models provided robust security through re-identification. The membership inference attacks achieved an accuracy of nearly random guessing (50%), and the linkage tests did not match the synthetic records with any real patient, with high confidence. With its differential privacy mechanism, Diffusion EHR was shown to have the smallest estimated re-identification risk of all the considered models. Figure 4 shows the privacy performance across models, while Table 6 presents the corresponding privacy risk metrics.

Figure 4
Differential Privacy & Values for Each Generative Model (Lower ε Indicates Stronger Privacy Guarantees)



Note. Authors' analysis based on study data

Table 6 presents the privacy risk measure of each generative model (membership attack accuracy, linkage success rate, and differential privacy values).

Table 6
Privacy Risk Metrics

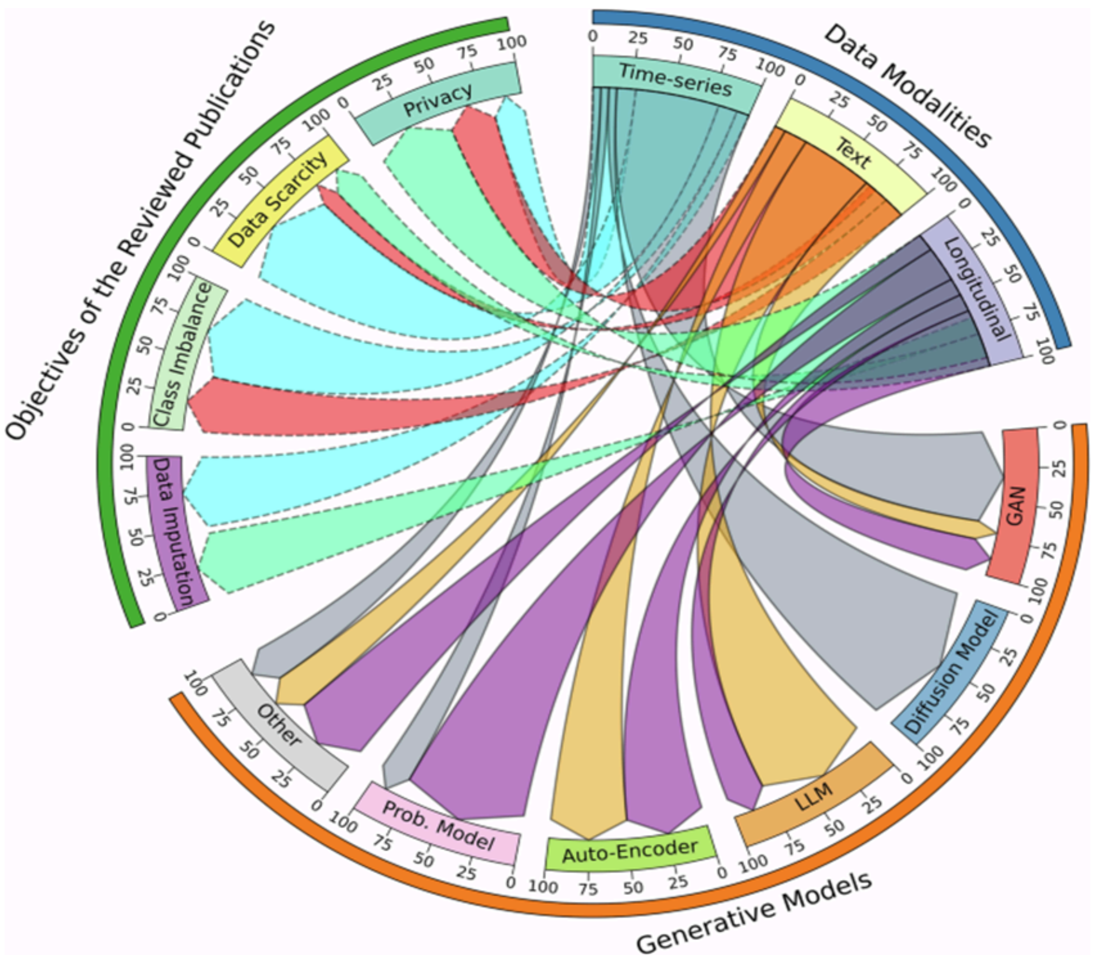
Model	Membership Attack Accuracy	Linkage Success Rate	Differential Privacy
MedGAN-2025	0.53	0.06	3.2
VAE-SeqHealth	0.51	0.05	2.9
Diffusion EHR	0.5	0.04	2.5

Case Study: Disease Prediction Using Synthetic EHRs

To identify the progression of chronic kidney disease, a targeted experiment using artificial datasets was conducted. Machine learning models trained on synthetic CKD data had similar performance in terms of the AUROC to those trained on real CKD data. Moreover, no re-identification events were noticed in any patients. Even experts in that field concurred that artificial journeys of patients reflected the clinical course of the illness, and the approach of abnormal laboratory values and regimens of therapy were also present, based on the expert judgment in the given study. Figure 5 presents the AUROC comparison for CKD prediction using real and synthetic data.

Figure 5

AUROC Comparison of CKD Prediction Using Real Versus Synthetic Data



Note. Authors' analysis based on study data.

Impact on Data Accessibility for Low-Resource Healthcare AI Projects

The fact that it is possible to produce large and demographically diverse artificial EHR data sets has a direct impact on the AI research in low-resource healthcare environments. The creation of sets of datasets reflecting rural and underserved populations enabled institutions that lacked a long history of EHRs to build competitive predictive models. It is instrumental in helping narrow the health disparities and in supporting global health AI efforts due to this democratization of access.

Discussion/Implications

The results of the current research indicate that generative AI is a feasible method to create synthetic EHRs to train medical AI. The fact that most generative models achieve downstream performance on par with their competitors in 2025 and the statistical similarity between synthetic and real datasets is high reflect the maturation of the generative architecture. Although the technology, to some extent, has not completely prohibited all the shortcomings of utilizing real-world data, it presents tremendous advantages in terms of accessibility, scalability, and ethical data management.

Implications for Medical AI Model Development

Artificial EHRs represent an approach to creating AI in the medical field. The datasets can be used to pre-train and validate models, eliminating the delays involved in obtaining institutional review board (IRB) approval or negotiating cross-institutional data sharing agreements, by mirroring the statistical and structural properties of real patient records. The results suggest that the hybrid formation of mixed synthetic and minimal real data can surpass the performance of models trained on either synthetic or real data alone, and in this case, of underrepresented patient groups (Hernandez et al., 2023). The implications of this are direct in terms of minimizing bias in algorithms and enhancing model generalization to a wide variety of healthcare settings. Additionally, the federation of institution-wide AI development enabled by the integration of synthetic EHRs into federated learning settings could potentially facilitate collaborative AI development without compromising sensitive patient data. This opens possibilities of training AI models on the global level, where only synthetic data will be provided by the participating institutions, which decreases legal and infrastructural issues. Diffusion EHR was found to be the best model in terms of privacy in relation to the other models assessed, as shown in Figure 4, with its lower differential privacy ε value.

Benefits and Limitations of Synthetic EHRs

The benefits of synthetic EHRs include:

- **Scalability**: One of the advantages of large-scale AI training is the capability to create datasets that are practically limitless in size.
- **Privacy Preservation**: The artificial nature of the information removes all explicitly identifying characteristics of patients, thus lowering the risk of re-identification.
- **Bias Mitigation**: Minority demographics and rare conditions may be oversampled to establish more balanced datasets.
- **Faster Iteration**: By avoiding bottlenecks in data access, research and model development cycles are significantly accelerated.

But some limitations exist. Although the strength of statistical similarity metrics was considerable, some temporal and causal relationships in patient trajectories might be inaccurately reconstructed, particularly for complex clinical events. Moreover, practitioners may rely too heavily on synthetic data and not validate it sufficiently against reality, which can lead to a set of performance gaps when the model is put into practice. Additionally, the computational costs for training cutting-edge generative models, especially those based on diffusion architectures, are still relatively high, which means that advanced facilities, which are not always available in resource-limited locations, are needed.

Integration with Emerging Technologies (Federated Learning, Blockchain)

Combining federated learning and synthetic data opens the possibility of utilizing the synergy between these two technologies to train AI on heterogeneous systems without the need for centralized data. In such cases, synthetic data can be created on-site at each member location and merged via standard data models, allowing for the sharing of models to be jointly trained through federated protocols.

This reduces both the privacy risks and the governance burden, which are typically associated with federated AI. The aid of blockchain technology will be available for this, as it provides a transparent and immutable record of the creation of synthetic data, the activities of model training, and the achievement of privacy compliance (Lan et al., 2020). By deploying blockchain-anchored smart contracts, organizations will have the ability to control usage, verify the source of datasets, and ensure agreement with privacy consents that are mutually agreed upon. The new combined technologies may become the basis of a secure, global synthetic data trade system.

Ethical, Legal, and Social Implications (ELSI)

Ethically, synthetic EHRs offer solutions to numerous privacy issues surrounding patients, although they do not eliminate all risks of misuse. Synthetic datasets might capture biases even without the direct inclusion of identifiers or mirror patterns that serve to underrepresent a particular group of people. It requires constant surveillance and bias auditing. Synthetic data constitutes a grey area in legal terms, as most jurisdictions do not consider it to be protected health information (PHI). However, regulators are increasingly demanding disclosure of synthetic data generation techniques (Dave et al., 2024). Since researchers using synthetic EHRs have a greater representation in democratizing AI research, less well-funded institutions, non-profits, and low-resource organizations may easily utilize high-quality training data without the need for overly restrictive data-sharing contracts. The availability of synthetic data can only be accepted by people when there are proper explanations of how that data was developed, checked, and used.

Conclusion

Summary of Key Contributions

This study provides an in-depth analysis of the scope and achievements of generative AI in fabricating synthetic Electronic Health Records (EHRs) for medical AI training by 2025. The results show that the state-of-the-art generative architectures, in particular, GANs, VAEs, and diffusion models, are capable of generating synthetic data, which is similar to the actual patient data and aids in privacy protection.

Key contributions include:

- **Quantitative Validation**: Empirical evidence suggests that artificially generated electronic health record (EHR) models trained on synthetic data can achieve predictive performance comparable to that of models trained on real data, reaching 96-98% of the latter’s accuracy across various clinical tasks.

- **Privacy Preservation**: Showed resilience to re-identification attempts, as risk values were near the range of statistical randomness after the application of privacy-preserving techniques.

- **Hybrid Dataset Advantage**: Findings underscore that the use of synthetic data, along with real data, enables higher model generalization, most notably in those subpopulations that have been less represented.

- **Applicability to Low-Resource Settings**: Synthetic EHRs provide a means to practically expand the research area of AI in places where health digital infrastructure is limited or absent. In this way, they back health equity worldwide.

- **Integration Pathways**: Described how to integrate synthetic data generation into federated learning and blockchain ecosystems to have a safe, collaborative AI development.

Recommendations for Future Work

Despite the evidence highlighting the capability of artificial EHRs for a wide range of AI training applications, they still require groundbreaking research and improvements in their quality:

1. **Enhancing Temporal Fidelity**: Enhance the representation of complex changes over time and causal relationships in synthetic patient trajectories to more accurately reflect rare clinical events.

2. **Bias Auditing Frameworks**: Establish standardized tools for identifying biases in demographics, socioeconomics, and clinical areas and for generating a bias-free dataset.

3. **Regulatory Standards**: Collaborate with legislators to develop official regulations that incorporate healthcare data generated through the use of synthetic methods, verification, and ethical considerations.

4. **Multi-Modal Expansion**: Enhance generation capabilities to facilitate the seamless integration of imaging, genomic, and sensor data, as well as structured electronic health records, for precision medicine research.

5. **Real-World Clinical Trials**: Perform evaluations of AI models that are trained on synthetic or hybrid data with a view to their safety and performance when introduced into the healthcare environment.

These are the steps that the community of AI in healthcare could take to realize the complete capacity of generative AI to produce a synthetic EHR. The pace of that change would be phenomenal, the outreach broader, and the systems would be not only useful but fair in terms of distribution across different patient groups.

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References

Achterberg, J. L., Haas, M. R., & Spruit, M. R. (2024). On the evaluation of synthetic longitudinal electronic health records. *BMC Medical Research Methodology, 24*(1), 181. https://doi.org/10.1186/s12874-024-02304-4

Chen, Y., & Esmaeilzadeh, P. (2024). Generative AI in medical practice: In-depth exploration of privacy and security challenges. *Journal of Medical Internet Research*, *26*, e53008. https://doi.org/10.2196/53008

Dave, T., Athaluri, S. A., & Singh, S. (2024). Generative AI in healthcare: An implementation science informed translational path on application, integration and governance. *Implementation Science, 19*(1), 27. https://doi.org/10.1186/s13012-024-01357-9

Ghosheh, G. O., Li, J., & Zhu, T. (2024). A survey of generative adversarial networks for synthesizing structured electronic health records. *ACM Computing Surveys, 56*(6), 1–34. https://doi.org/10.1145/3636424

Goncalves, A., Ray, P., Soper, B., Stevens, J., Coyle, L., & Boyd, A. (2020). Generation and evaluation of synthetic patient data. *BMC Medical Research Methodology, 20*(1), 108. https://doi.org/10.1186/s12874-020-00977-1

Hernandez, M., Epelde, G., Alberdi, A., & Cilla, R. (2023). Synthetic data generation: State of the art in health care domain. *Computer Science Review, 48*, 100546. https://doi.org/10.1016/j.cosrev.2023.100546

Hernandez, M., Epelde, G., Alberdi, A., Cilla, R., & Rankin, D. (2022). Synthetic data generation for tabular health records: A systematic review. *Neurocomputing, 493*, 28–45. https://doi.org/10.1016/j.neucom.2022.04.053

Lan, L., You, L., Zhang, Z., Fan, Z., Zhao, W., Zeng, N., Chen, Y., & Zhou, X. (2020). Generative adversarial networks and its applications in biomedical informatics. *Frontiers in Public Health, 8*, 164. https://doi.org/10.3389/fpubh.2020.00164

Li, J., Cairns, B. J., Li, J., & Zhu, T. (2023). Generating synthetic mixed-type longitudinal electronic health records for artificial intelligent applications. *npj Digital Medicine, 6*(1), 98. https://doi.org/10.1038/s41746-023-00834-7

Li, R., Tian, Y., Shen, Z., Li, J., Li, J., Ding, K., & Li, J. (2023). Improving an electronic health record–based clinical prediction model under label deficiency: Network-based generative adversarial semisupervised approach. *JMIR Medical Informatics, 11*(1), e47862. https://doi.org/10.2196/47862

Loni, M., Kangavari, M. R., & Alinejad-Rokny, H. (2025). A review on generative AI models for synthetic medical text, time series, and longitudinal data. *npj Digital Medicine, 8*(1), 95. https://doi.org/10.1038/s41746-024-01409-w

Pezoulas, V. C., Zaridis, D. I., Mylona, E., Androutsos, C., & Fotiadis, D. I. (2024). Synthetic data generation methods in healthcare: A review on open-source tools and methods. *Computational and Structural Biotechnology Journal, 25*, 2892–2910. https://doi.org/10.1016/j.csbj.2024.07.005

Yan, C., Yan, Y., Wan, Z., Zhang, Z., Omberg, L., Guinney, J., Mooney, S. D., & Malin, B. A. (2022). A multifaceted benchmarking of synthetic electronic health record generation models. *Nature Communications, 13*(1), 7609. https://doi.org/10.1038/s41467-022-35295-1

Yan, C., Zhang, Z., Nyemba, S., & Li, Z. (2024). Generating synthetic electronic health record data using generative adversarial networks: Tutorial. *JMIR AI, 3*, e52615. https://doi.org/10.2196/52615

Zhang, P., & Kamel Boulos, M. N. (2023). Generative AI in medicine and healthcare: Promises, opportunities and challenges. *Future Internet*, *15*(9), 286. https://doi.org/10.3390/fi15090286

The Role of Demographic Factors and Entrepreneurial Exposure in Shaping Faculty Entrepreneurial Mindset

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Abstract

The entrepreneurial mindset is increasingly emphasized in higher education, yet faculty perspectives remain underexplored. The purpose of this study is to explore how demographic factors and entrepreneurial exposure influence the entrepreneurial mindset among the faculty of higher educational institutions in Nepal. Employing a quantitative research method and a cross-sectional design, data were collected through an online survey of 248 faculty members selected, using purposive and snowball sampling. Through non-parametric tests (Mann–Whitney U, Kruskal–Wallis H) and CHAID decision tree methods using SPSS 26.0, results indicated that demographic and entrepreneurial experience shaped the entrepreneurial mindset of the faculty. Specifically, the result showed that faculty qualification, teaching level, and participation in entrepreneurship workshops emerged as the most influential variables, demonstrating consistency across multiple entrepreneurial mindset dimensions. While gender, age, faculty qualification, participation in entrepreneurship workshops, experience in teaching entrepreneurship courses, and teaching level show a significant impact on entrepreneurial mindset, teaching experience and the entrepreneurial course studied have no impact on their mindset. The study highlights the combined role of demographics and exposure in shaping faculty entrepreneurial mindset, offering insights for professional development and institutional policy to promote entrepreneurial thinking.

Keywords: Entrepreneurial mindset, demographic factors, entrepreneurial exposure, risk-taking, innovativeness, autonomy, proactiveness, passion

Introduction

Entrepreneurial mindset has gained scholarly attention that enables individuals to identify opportunities, take initiative, and create innovative solutions in uncertain environments (Hölzner & Halberstadt, 2023; Santos et al., 2017). The entrepreneurial mindset is a multidisciplinary construct and increasingly seen as essential not only for students and entrepreneurs but also for educators, researchers, and professionals across fields (Bosman & Fernhaber, 2018; Bosman & Fernhaber, 2021; Kuratko et al., 2021).

Higher education is shifting, changing, and facing unprecedented challenges (Ramaley, 2014); institutions are investing in their human capital to remain competitive and market-driven through innovating in the teaching and learning process (Ostojic & Leko Simic, 2021). Entrepreneurship studies have been increasing in the academic context (Hayter et al., 2018), and higher education institutions are developing the infrastructure, entrepreneurship curriculum, and business incubation to promote entrepreneurship (Jurgelevicius et al., 2025). In this mission, active faculty involvement is essential (Abo-Khalil, 2024). They play a significant role in making institutions sustainable and relevant to the market (Kearney & Meynhardt, 2016). Faculty members play a vital role in shaping students' entrepreneurial thinking and fostering an institutional culture that supports innovation. Faculties interact with students, deliver course material, and provide mentorship; thus, their mindset and how they cultivate entrepreneurial thinking have an impact on the development of entrepreneurial aspirations in students.

Davis et al. (2016) defined the entrepreneurial mindset as the "constellation of motives, skills, and thought processes that distinguish entrepreneurs from non-entrepreneurs and contribute to entrepreneurial success" (p. 22). In the literature, the entrepreneurial mindset was broadly discussed as skills and attitudes, such as risk-taking, autonomy, innovativeness, proactiveness, and passion (Dinh et al., 2022; Imran et al., 2019; Jung & Lee, 2020). It is noteworthy to state that the entrepreneurial mindset and the entrepreneurial orientation dimension are similar (Krueger & Sussan, 2017); however, the difference is that entrepreneurs' orientation has been widely considered for the firm level, while the entrepreneurial mindset is on an individual level. An entrepreneurial mindset is an individual-level cognitive and behavioral pattern that reflects how a person thinks, perceives opportunities, and acts entrepreneurially (Daspit et al., 2023).

Despite the acknowledged importance of faculty role in promoting entrepreneurship, there is a research gap about how demographic factors and entrepreneurial exposure influence their entrepreneurial mindset. The literature has highlighted that personality traits and situational factors have been considered to study the development of the entrepreneurship phenomenon (Kerr et al., 2017; Najev Čacija et al., 2023; Salmony & Kanbach, 2022). According to Ajzen (2002), demographic factors influence attitudes about one's own behavior and its normative consideration; thus, it is essential to understand how demographic factors and prior entrepreneurial exposure impact the entrepreneurial mindset.

The mindset is based on their past engagement and experience. The researcher has considered demographic factors to discuss entrepreneurship (Liang et al., 2014) and its dimensions, such as entrepreneurial intention (Jovicic Vukovic et al., 2020; Najev Cacija et al., 2023; Nguyen, 2018; Ozyilmaz, 2011; Paray & Kumar, 2020), entrepreneurial orientation (Abidi et al., 2022; Meilani & Ginting, 2018), entrepreneurial performance (Gunawan, 2024; Tasman et al., 2023), entrepreneurial motivation (Sarmah et al., 2022), entrepreneurship education (Justus, 2021; Sharma & Ahmad, 2023), intrapreneurship behavior (Adachi & Hisada, 2017; Shian et al., 2022). The literature shows that limited research has been conducted to determine whether and how demographic factors operate among higher education faculty members and their influence on entrepreneurial behavior (Abidi et al., 2022; Rodrigues et al., 2019). Research suggests that the impact of demographic factors on the formation of an entrepreneurial mindset has received limited attention in the academic context (Jung & Lee, 2020), whereas universities are spending a lot of resources in developing entrepreneurial cultures.

This gap is particularly relevant in contexts where higher education institutions are striving to embed entrepreneurship in their curricula and research agendas yet often encounter uneven faculty engagement (Abidi et al., 2022; Westover, 2025). The entrepreneurial mindset of faculty is the core of the development of entrepreneurial culture. Understanding how faculty demographic characteristics and entrepreneurial exposure influence their mindset can provide valuable insights for designing faculty development programs, tailoring institutional policies, and fostering a stronger entrepreneurial ecosystem within universities.

Thus, the study seeks to bridge this gap by exploring the extent to which faculty demographic factors and entrepreneurial exposure serve as determinants of entrepreneurial mindset. Specifically, it aims to analyze whether variations in age, gender, educational attainment, entrepreneurial exposure, and teaching experience are associated with differences in entrepreneurial mindset or not.

Literature Review and Hypothesis Development

Entrepreneurial Mindset

Robinson and Gough (2020) mentioned the entrepreneurial mindset as a “poorly defined concept” that is yet to be fully developed and must be researched further in entrepreneurship literature. Oestreich (2023) defined the entrepreneurial mindset as individual traits for thinking outside the box, whereas Davis et al. (2016) described it as a personality trait and set of skills that guide individuals to become innovative. Also, Ireland et al. (2003) defined entrepreneurial mindset as “the ability to rapidly sense, act, and mobilize, even under uncertain conditions." Further, Dinh et al. (2022) conducted a systematic literature review to identify the dimensions of entrepreneurial mindset; some of the dominant traits include opportunity seeking, action orientation, working in uncertainty, risk-taking, practices, autonomy, problem-solving, innovativeness, resilience, and value creation.

Further, researchers developed different instruments, such as the Kern entrepreneurial engineering network framework (Gorlewicz & Jayaram, 2019), the entrepreneurial mindset profile (Davis et al., 2016), the mindset scale (Mathisen & Arnulf, 2014), and the entrepreneurial orientation scale (Toledano & Urbano, 2008; Krueger & Sussan, 2017) to measure entrepreneurial mindset. As per the study conducted by Dinh et al. (2022), in the context of an educational setting, the entrepreneurial mindset of the faculty members can be defined as the skills and attitudes on how they approach curriculum design, strategy for classroom management, engage in research with societal impact, bring new ways to teaching and learning pedagogy, and mentor students toward entrepreneurial activity.

These studies concluded that the entrepreneurial mindset of faculty can be examined across five dimensions: risk-taking (willingness to engage in uncertain ventures), autonomy (ability to make independent decisions), innovativeness (generating and implementing creative ideas), proactiveness (anticipating and acting on opportunities), and passion (strong commitment and intrinsic motivation). These attitudinal dimensions will help explore how faculty embody entrepreneurial traits and engage with entrepreneurship initiatives (Davis et al., 2016).

Gender and Entrepreneurial Mindset

Gender has been one of the most widely examined demographic factors in entrepreneurship research (Samsam et al., 2025). Many studies report that men tend to express stronger entrepreneurship behavior (Cacija et al., 2023; Reynolds et al., 2002; Sarmah et al., 2022). The study conducted by Alhosseiny and Ahmad (2022) and Justus (2021) concluded that male faculty have a more entrepreneurial mindset than female faculty. However, Srivastava (2025) shows that women students have a higher entrepreneurial mindset in a major dimension, and Kaya and Yuksel (2022) show that female faculty have a higher growth mindset. Smith et al.'s (2016) study shows no significant difference between men and women regarding entrepreneurship. Degefu and Verma (2025) concluded that gender has a significant impact on the entrepreneurial mindset of the students and how they pursue opportunities in the field. Further, Samsami et al (2024) found that gender shaped the mindset, but the contextual support system influenced their relationship. Despite the growing literature in the entrepreneurial mindset and entrepreneurship field, only limited literature has focused on studying how gender shapes the entrepreneurial mindset of the faculty (Abidi, 2022). The current research evidence remains inconclusive, making it important to explore how gender influences entrepreneurial mindset in faculty populations.

H1: There is a statistically significant difference in the entrepreneurial mindset and its five dimensions based on gender.

Age and Entrepreneurial Mindset

The relationship between age and entrepreneurship has been widely examined among students and working professionals. Abidi et al. (2022) confirmed that faculty age plays a vital role in shaping their mindset to engage in developing new pedagogical and teaching-learning strategies that enhance their entrepreneurial orientation and performance.

Age is often linked to entrepreneurial behavior, with younger individuals generally seen as more open to risk and innovation (Chaudhary, 2017). A study conducted by Muhammed and Henry (2024), among university students, shows that age has a significant relationship with the development of their entrepreneurial mindset. However, research conducted by Degefu and Verma (2025) and Nguyen (2018) did not show any significant relationship with entrepreneurial intention, whereas Bohlmann et al. (2017) confirmed that age was negatively related to entrepreneurial activity. Syed et al. (2024) examined the relationship between age and entrepreneurship by analyzing a literature review and concluded that age has a direct and indirect role in defining the entrepreneurship characteristics. Prior research is dominant in understanding the role of students' age in determining their entrepreneurship intention. These findings highlight the need to further examine the role of age in shaping faculty entrepreneurial mindset.

H2: There is a statistically significant difference in the entrepreneurial mindset and its five dimensions based on age.

Years of Teaching Experience and Entrepreneurial Mindset

Teaching experience has been recognized as a key factor influencing faculty mindset and their innovation intention (Fernández-Cruz & Rodríguez-Legendre, 2021). Faculty with extensive teaching experience may have greater confidence, which can encourage an entrepreneurial mindset in terms of curriculum design and innovation (Abidi, 2022).

Kaya and Yuksel (2022) showed that senior faculty possess higher entrepreneurial characteristics compared to new faculty, aligning with Santos et al. (2017), Alhammadi et al. (2022), and Kuratko et al. (2021) studies. Although some studies suggest a positive relationship between teaching experience and mindset, research that directly examines years of teaching experience in higher education as a predictor of entrepreneurial mindset remains limited.

H3: There is a statistically significant difference in the entrepreneurial mindset and its five dimensions based on teaching experience.

Academic Qualification and Entrepreneurial Mindset

The study by Alhosseiny and Ahmad (2022) concluded that faculty qualifications are significant in learning and developing faculty entrepreneurial mindset. Faculty members with higher degrees can enhance their ability to identify opportunities, innovate, and mentor students in entrepreneurial pursuits (Hahn et al., 2017; Muange & Kiptoo, 2020). For faculty, this dynamic is particularly relevant, as qualifications shape their orientation toward research, teaching, and external engagement. However, Abidi (2022) and Pinto et al. (2024) found that the level of the highest academic qualification does not have a significant relationship with innovative behavior. This suggests that while higher qualifications can enrich an entrepreneurial mindset through expertise and networks, they may also foster conservatism in teaching and research approaches.

H4: There is a statistically significant difference in the entrepreneurial mindset and its five dimensions based on academic qualification.

Entrepreneurship Courses, Workshops, and Entrepreneurial Mindset

Entrepreneurship education, whether through formal courses or short-term workshops, has been widely acknowledged as a driver of entrepreneurial mindset development, as it shapes individuals' ability to recognize opportunities, innovate, and engage in proactive problem-solving, which are key components of the entrepreneurial mindset (Overwien et al., 2024; Wardana et al., 2020). Similarly, the curriculum and content of entrepreneurship skills development and training and coaching programs have been shown to foster an entrepreneurial mindset, self-efficacy, and skills among students (De la Gala-Velásquez et al., 2024; Shetty et al., 2024; Zulkifli et al., 2025). While most evidence comes from student populations, the results underscore the potential benefits of similar interventions for faculty members as well.

H5: There is a statistically significant difference in the entrepreneurial mindset and its five dimensions based on the entrepreneurship course studied

H6: There is a statistically significant difference in the entrepreneurial mindset and its five dimensions based on experience in entrepreneurship workshop participation.

Teaching Entrepreneurship Courses and Entrepreneurial Mindset

Teaching entrepreneurship courses plays a pivotal role in shaping the entrepreneurial mindset of higher education faculty. Neergard and Roald (2025) noted that educators without prior experience in teaching entrepreneurship courses often lead them to believe they lack the necessary competence and attitude to teach the subject effectively. Research has shown that faculty who are involved in teaching entrepreneurship courses build confidence and a professional identity in this role, enhancing their entrepreneurial motivation and prompting faculty to rethink and incorporate mindset attributes into their practice (Brush et al., 2024; Nadelson et al., 2018). Neergård and Roald (2024) confirmed that the faculty's ability to teach entrepreneurship influences their entrepreneurial position and attitude. This indicates that repeated involvement in teaching entrepreneurship can gradually cultivate a faculty entrepreneurial mindset, as teaching practice, reflection, and exposure to evolving entrepreneurial ecosystems reinforce entrepreneurial thinking over time. While the research highlighted the role of teaching entrepreneurship courses, the research is very limited in the higher education sector that explicitly examines the role of teaching entrepreneurship and innovation-related courses in shaping the mindset of the faculty.

H7: There is a statistically significant difference in the entrepreneurial mindset and its five dimensions based on experience in teaching entrepreneurship courses.

Teaching Level and Entrepreneurial Mindset

Faculty teaching at different academic programs utilize varying pedagogical and andragogical approaches. For example, Nakamura and Csikszentmihalyi (2004) discussed that faculty teaching at the undergraduate level tends to focus on foundational knowledge, scaffolded skill-building, and motivation. In contrast, faculty teaching at the master’s level often connects students’ prior professional experience with the content, which encourages application-oriented, problem-based, and practice-focused approaches that align closely with entrepreneurial pedagogy (Rodrigues, 2023).

H8: There is a statistically significant difference in the entrepreneurial mindset and its five dimensions based on teaching level.

Methods and Materials

This study used a quantitative, descriptive cross-sectional survey design to collect data from faculties currently teaching undergraduate and graduate-level programs in Nepal. A purposive and snowball sampling methodology was used to reach targeted participants, yielding 248 valid responses. Although these sampling methods enabled access to a wider network of faculty respondents, they may introduce selection bias and limited generalizability.

To measure the attitudinal dimension of entrepreneurial mindset, a total of five dimensions, i.e., risk-taking, innovativeness, autonomy, proactiveness, and passion, were adapted from Davis et al. (2021), rated on a five-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree. Demographic variables, such as age, gender, years of teaching experience, faculty teaching position, highest academic qualification, core subject area, and institutional affiliation, were measured using categorical options. Entrepreneurial exposure was assessed through dichotomous (yes/no) measures capturing whether respondents had (a) studied an entrepreneurship course, (b) attended an entrepreneurship workshop, and (c) taught entrepreneurship or innovation-related courses.

The data from this study were examined using the statistical package for the Social Sciences (SPSS 26.0). The reliability and validity were examined. Normality has been tested using the Kolmogorov–Smirnov test and the Shapiro–Wilk test. The result shows that data is not normally distributed (Kolmogorov–Smirnov test, df = 253, *p*-value = 0.00; and Shapiro–Wilk test, df = 253, *p*-value = 0.00); thus, non-parametric tests were employed. The Mann–Whitney U test was used to compare entrepreneurial mindset across binary groups, while the Kruskal–Wallis H test was applied for multi-group comparisons. Chi-square automatic interaction detection (CHAID) was used to generate a decision tree to identify complex interactions among predictors that influence the entrepreneurial mindset of faculty.

Results

Item Analysis

Table 1 summarizes faculty responses across the five dimensions of entrepreneurial mindset. Overall, the mean entrepreneurial mindset score was 3.77 (*SD* = 0.74), indicating a generally positive orientation among faculty members. The result showed that, among five dimensions of entrepreneurial mindset, risk-taking scored the lowest (*M* = 3.53, *SD* = 0.88). While 64.4% of faculty showed some willingness to take risks, about 45% do not show a positive risk-taking propensity. This shows that while some faculty are willing to take risks, many are more cautious and prefer safer approaches in their academic work.

Innovativeness is the highest mean (*M* = 4.03, *SD* = 0.88). More than 80% of respondents agreed or strongly agreed that rigid and structured tasks feel boring, reflecting a strong preference for flexibility and innovation in their academic roles. Autonomy showed a moderate level (*M* = 3.58, *SD* = 0.97). Although many faculty members expressed a desire to carry out their work in their own way, nearly 40% remained neutral or disagreed.

Proactiveness was relatively strong (*M* = 3.86, *SD* = 0.88). About 70% of faculty reported making decisions quickly, pointing to a readiness to act rather than delay. Passion was also high (*M* = 3.84, *SD* = 0.82). Over 70% agreed or strongly agreed that they are passionate about their work, highlighting intrinsic motivation and engagement in their academic careers. The table concludes that faculty are motivated, proactive, and like to explore opportunities, but they are less inclined to take risks.

Table 1
Descriptive Item Analysis

Question	*M*	St. D	*SD*	D	N	A	SA
Risk-taking: I am willing to take a certain amount of risk to achieve real success	3.53	0.87	-	14.2%	30.4%	43.9%	11.5%
Innovativeness: I find it boring to work on clearly structured tasks	4.03	0.88	1.6%	5.5%	11.1%	51.8%	30.0%
Autonomy: I like to work things out my way	3.58	0.97	.8%	15.4%	26.1%	40.7%	17.0%
Proactiveness: I tend to make decisions quickly	3.86	0.87	.8%	6.7%	21.3%	48.2%	22.9%
Passion: I am passionate about the work that I do	3.84	0.82	.8%	5.1%	22.5%	52.2%	19.4%
Entrepreneurial Mindset Average	3.76	0.74					

Note. M- mean, St.D- standard deviation, *SD*- strongly disagree, D- disagree, N- neutral, A- agree, SA- strongly agree.

Reliability and Validity

The purpose of the study is to measure how demographic and entrepreneurial exposure shape the entrepreneurial mindset. The entrepreneurial mindset was measured using a previously validated five-item scale.

The reliability of the entrepreneurial mindset was tested using Cronbach's alpha value. The value of 0.809 confirms that the instrument is reliable for measuring faculty entrepreneurial mindset.

The factor analysis was performed, and KMO and Bartlett's Test; the result showed that the Kaiser-Meyer-Olkin measure of sampling adequacy value is 0.855. Bartlett's Test of Sphericity was significant, $\chi^2(10) = 741.829$, $p < .001$, confirming that the variables were sufficiently correlated to proceed with factor analysis.

The average variance extracted for the construct was 0.697, exceeding the recommended threshold of 0.50, indicating strong convergent validity.

Gender and Entrepreneurial Mindset

The Kruskal–Wallis test was performed to assess whether faculty members' entrepreneurial mindset differed by gender. Table 2 shows statistically significant differences in overall faculty entrepreneurial mindset across gender groups ($\chi^2 = 12.200$, $df = 2$, $p = 0.002$). Male faculty ($N = 172$) exhibited the highest mean rank (134.93) and mean score ($M = 3.87$, $SD = 0.05$), indicating a stronger entrepreneurial mindset compared to female faculty ($N = 63$, mean rank = 102.30, $M = 3.57$, $SD = 0.09$) and those who preferred not to disclose their gender ($N = 13$, mean rank = 94.04, $M = 3.31$, $SD = 0.28$). The significant test results show that there are significant differences in the overall entrepreneurial mindset of faculty members.

The findings indicate statistically significant gender-based differences in three entrepreneurial mindset areas. First, male faculty reported a greater willingness to take risks in pursuit of success ($\chi^2 = 12.496$, $df = 2$, $p = 0.002$) with higher mean ranks (134.49) compared to females (103.60) and prefer not to say (93.65). Male respondents demonstrated a stronger preference for autonomy, expressing a greater tendency to work in their own way ($\chi^2 = 17.722$, $df = 2$, $p < 0.001$). Similarly, the overall measure of faculty entrepreneurial mindset was higher among male faculty (mean rank = 134.93) relative to females (102.30) and prefer not to say (94.04), with the difference reaching statistical significance ($\chi^2 = 12.200$, $df = 2$, $p = 0.002$).

There were no statistically significant gender differences found in attitudes toward clearly structured tasks ($\chi^2 = 4.103$, $p = 0.129$), speed of decision-making ($\chi^2 = 5.183$, $p = 0.055$), and passion for work ($\chi^2 = 4.988$, $p = 0.082$).

Table 2

Descriptive Statistics of Faculty Entrepreneurial Mindset and the Kruskal–Wallis Test Results Regarding Gender

	Gender	*N*	Mean Rank	Mean	*SD*	K-W Test	Decision
Risk Taking	Male	172	134.49	3.65	0.064	0.002 (χ^2 = 12.496; *df* = 2)	Reject the null hypothesis
	Female	63	103.60	3.24	0.112		
	Prefer not to say	13	93.65	3.08	0.288		
Innovativeness	Male	172	127.82	4.09	0.065	0.129 (χ^2 = 4.103; *df* = 2)	Retain the null hypothesis
	Female	63	122.58	4.00	0.113		
	Prefer not to say	13	89.88	3.46	0.332		
Autonomy	Male	172	136.60	3.74	0.072	0 (χ^2 = 17.722; *df* = 2)	Reject the null hypothesis
	Female	63	98.65	3.21	0.116		
	Prefer not to say	13	89.69	3	0.32		
Proactiveness	Male	172	131.30	3.95	0.063	0.055 (χ^2 = 5.183; *df* = 2)	Retain the null hypothesis
	Female	63	109.63	3.65	0.118		
	Prefer not to say	13	106.54	3.54	0.332		
Passion	Male	172	130.57	3.94	0.058	0.082 (χ^2 = 4.988; *df* = 2)	Retain the null hypothesis
	Female	63	112.17	3.73	0.107		
	Prefer not to say	13	103.96	3.46	0.332		
Faculty Entrepreneurial Mindset	Male	172	134.93	3.87	0.05	0.002 (χ^2 = 12.200; *df* = 2)	Reject the null hypothesis
	Female	63	102.30	3.57	0.09		
	Prefer not to say	13	94.04	3.31	0.28		
	Total	248					

Age and Entrepreneurial Mindset

Table 3 results show that there is no statistically significant difference in faculty entrepreneurial mindset among age groups ($\chi^2 = 3.075$; $df = 3$; $p = 0.380$). However, there is a statistically significant difference in faculty perceptions regarding the monotony of structured tasks across age groups ($\chi^2 = 10.117$; $df = 3$; $p = 0.018$), with faculty (31–40 years) showing high flexibility and creativity, whereas older faculty (above 50 years) showed lower scores; this shows that they are more aligned with structured work. Similarly, decision-making tendencies varied significantly with age ($\chi^2 = 9.612$; $df = 3$; $p = 0.022$), where mid-career faculty (31–40 and 41–50 years) reported quicker decision-making compared to their younger or older counterparts. Passion for work also demonstrated a strong age-related difference ($\chi^2 = 17.771$; $df = 3$; $p < 0.001$), with faculty aged 41–50 years showing the highest levels of passion, whereas the oldest group (above 50 years) reported lower levels. There are no significant differences between age groups in willingness to take risks ($\chi^2 = 1.492$; $df = 3$; $p = 0.684$) and autonomy in working style ($\chi^2 = 1.717$; $df = 3$; $p = 0.633$).

Table 3
Descriptive Statistics of Faculty Entrepreneurial Mindset and the Kruskal–Wallis Test Results Regarding Age

	Age	*N*	Mean Rank	Mean	*SD*	K-W Test	Decision
Risk Taking	20-30 Years	64	119.38	3.42	0.115	0.684 (χ^2 = 1.492; df = 3)	Retain the null hypothesis
	31-40 Years	128	127.83	3.56	0.081		
	41-50 Years	37	117.04	3.46	0.083		
	50 +Years	19	133.84	3.63	0.256		
Innovativeness	20-30 Years	64	144.14	4.33	0.074	0.018 (χ^2 = 10.117; df = 3)	Reject the null hypothesis
	31-40 Years	128	121.70	3.98	0.084		
	41-50 Years	37	114.18	4.03	0.072		
	50 +Years	19	97.34	3.42	0.336		
Autonomy	20-30 Years	64	119.41	3.50	0.120	0.633 (χ^2 = 1.717; df = 3)	Retain the null hypothesis
	31-40 Years	128	122.77	3.55	0.093		
	41-50 Years	37	136.73	3.73	0.100		
	50 +Years	19	129.47	3.63	0.256		
Proactiveness	20-30 Years	64	112.70	3.73	0.098	0.022 (χ^2 = 9.612; df = 3)	Reject the null hypothesis
	31-40 Years	128	133.88	3.97	0.081		
	41-50 Years	37	129.91	3.97	0.082		
	50 +Years	19	90.58	3.26	0.295		
Passion	20-30 Years	64	103.95	3.64	0.101	0.000 (χ^2 = 17.771; df = 3)	Reject the null hypothesis
	31-40 Years	128	130.57	3.92	0.072		
	41-50 Years	37	153.07	4.22	0.069		
	50 +Years	19	97.21	3.47	0.258		
Faculty Entrepreneurial Mindset	20-30 Years	64	116.79	3.73	0.07	0.380 (χ^2 = 3.075; df = 3)	Retain the null hypothesis
	31-40 Years	128	128.58	3.80	0.07		
	41-50 Years	37	133.39	3.88	0.04		
	50 +Years	19	105.68	3.48	0.27		
	Total	248					

Teaching Experience and Entrepreneurial Mindset

Table 4 presents the results of the Kruskal–Wallis test examining differences in faculty entrepreneurial mindset with the levels of teaching experience. There are significant differences among experiences on three individual mindset dimensions, i.e., risk-taking (χ^2 = 9.707, df = 4, p < 0.05), openness to novelty (χ^2 = 16.901, df = 4, p < 0.01), and passion for work (χ^2 = 21.573, df = 4, p < 0.001). The result shows no significant differences in the autonomy dimension (χ^2 = 5.024, df = 4, p > 0.05) and quick decision-making (χ^2 = 2.349, df = 4, p > 0.05). In the overall faculty entrepreneurial mindset, there are no significant differences in relation to the faculty teaching experiences (χ^2 = 7.255, df = 4, p > 0.05). The descriptive table shows faculty with above 5 years of teaching experience reported higher scores in overall entrepreneurial mindset (M = 3.85) as well as in risk-taking dimension (M = 3.76), autonomy (M = 3.73), and quick decision-making (M = 3.95), whereas passion for work is highest in the faculty whose teaching experience is above 10 years (M = 4.09).

Table 4

Descriptive Statistics of Faculty Entrepreneurial Mindset and the Kruskal–Wallis Test Results Regarding Teaching Experience

	Teaching Experience	*N*	Mean Rank	Mean	*SD*	K-W Test	Decision
Risk Taking	0-2 Years	59	108.36	3.32	0.112	0.046 (χ^2 = 9.707; *df* = 4)	Reject the null hypothesis
	2- 5 years	49	117.26	3.43	0.12		
	5-7 years	41	143.77	3.76	0.143		
	7-10 years	35	117.21	3.43	0.111		
	10+ years	64	136.56	3.66	0.122		
Innovativeness	0-2 Years	59	127.35	4.15	0.076	0.002 (χ^2 = 16.901; *df* = 4)	Reject the null hypothesis
	2- 5 years	49	150.03	4.37	0.104		
	5-7 years	41	127.57	4.02	0.158		
	7-10 years	35	91.70	3.69	0.114		
	10+ years	64	118.30	3.86	0.142		
Autonomy	0-2 Years	59	117.66	3.51	0.129	0.285 (χ^2 = 5.024; df = 4)	Retain the null hypothesis
	2- 5 years	49	118.91	3.51	0.131		
	5-7 years	41	136.13	3.73	0.14		
	7-10 years	35	110.86	3.37	0.136		
	10+ years	64	135.09	3.67	0.143		
Proactiveness	0-2 Years	59	133.89	4.02	0.085	0.672 (χ^2 = 2.349; *df* = 4)	Retain the null hypothesis
	2- 5 years	49	117.34	3.78	0.128		
	5-7 years	41	128.37	3.95	0.121		
	7-10 years	35	124.90	3.91	0.095		
	10+ years	64	118.63	3.67	0.149		
Passion	0-2 Years	59	96.89	3.56	0.094	0.000 (χ^2 = 21.573; *df* = 4)	Reject the null hypothesis
	2- 5 years	49	118.30	3.84	0.089		
	5-7 years	41	122.55	3.8	0.136		
	7-10 years	35	135.79	4.03	0.112		
	10+ years	64	149.78	4.09	0.123		
Faculty Entrepreneurial Mindset	0-2 Years	59	108.84	3.71	0.07	0.123 (χ^2 = 7.255; *df* = 4)	Retain the null hypothesis
	2- 5 years	49	123.31	3.78	0.09		
	5-7 years	41	139.62	3.85	0.13		
	7-10 years	35	113.57	3.69	0.08		
	10+ years	64	136.14	3.79	0.13		
	Total	248					

Academic Qualification and Entrepreneurial Mindset

Table 5 presents the Kruskal–Wallis test results between entrepreneurial mindset dimensions across academic qualifications. There are statistically significant differences for the risk-taking dimension (χ^2 = 12.251, *df* = 3, $p < 0.01$), openness to novelty (χ^2 = 23.817, *df* = 3, $p < 0.001$), quick decision-making (χ^2 = 23.257, *df* = 3, $p < 0.001$), and passion for work (χ^2 = 38.326, *df* = 3, $p < 0.001$). Across all dimensions, faculty with a master's degree showed the highest mean score compared to other qualification statuses. There are no significant differences found for autonomy (χ^2 = 7.471, *df* = 3, $p > 0.05$), suggesting that the preference to work independently is consistent across qualifications. The overall entrepreneurial mindset shows a significant difference among faculty qualifications (χ^2 = 24.250, *df* = 3, $p < 0.001$), with Master's degree holders scoring the highest (*M* = 3.87), followed by Bachelor's (*M* = 3.51), PhDs (*M* = 3.23), and others (*M* = 3.02).

Table 5

Descriptive Statistics of Faculty Entrepreneurial Mindset and the Kruskal–Wallis Test Results Regarding Academic Qualification

	Qualification	*N*	Mean Rank	Mean	*SD*	K-W Test	Decision
Risk Taking	Bachelor	16	90.81	3.13	0.155	0.007	Reject the null
	Master	201	131.57	3.60	0.060	(χ^2 = 12.251;	hypothesis
	Phd	26	100.10	3.19	0.222	*df* = 3)	
	Other	5	75.00	3.00	0.000		
Innovativeness	Bachelor	16	122.13	4.13	0.085	0.000	Reject the null
	Master	201	132.50	4.16	0.054	(χ^2 = 23.817;	hypothesis
	Phd	26	81.77	3.19	0.272	*df* = 3)	
	Other	5	32.50	3.00	0.000		
Autonomy	Bachelor	16	122.88	3.63	0.221	0.058	Retain the null
	Master	201	129.27	3.63	0.068	(χ^2 = 7.471;	hypothesis
	PhD	26	98.27	3.19	0.222	*df* = 3)	
	Other	5	74.50	3.00	0.000		
Proactiveness	Bachelor	16	78.56	3.38	0.125	0.000	Reject the null
	Master	201	133.89	3.98	0.059	(χ^2 = 23.257;	hypothesis
	PhD	26	95.15	3.38	0.222	*df* = 3)	
	Other	5	46.50	3.00	0.000		
Passion	Bachelor	16	70.25	3.31	0.12	0.000	Reject the null
	Master	201	136.70	4.01	0.051	(χ^2 = 38.326;	hypothesis
	Phd	26	79.50	3.19	0.222	*df* = 3)	
	Other	5	41.50	3.10	0.000		
Faculty Entrepreneurial Mindset	Bachelor	16	80.63	3.51	0.06	0.000	Reject the null
	Master	201	134.86	3.87	0.05	(χ^2 = 24.250;	hypothesis
	Phd	26	87.46	3.23	0.22	*df* = 3)	
	Other	5	41.00	3.02	0.00		
	Total	248					

Entrepreneurship Courses Studied and Entrepreneurial Mindset

Table 6 shows the Mann–Whitney *U* test results on whether studying entrepreneurship courses has an impact on faculty entrepreneurial mindset. The results show there are significant differences in risk-taking (U = 6484.5, Z = –2.712, $p < 0.01$) and openness to novelty (U = 4531, Z = –3.443, $p < 0.01$). There are no significant differences for autonomy (U = 6005, Z = –0.239, $p > 0.05$), quick decision-making (U = 5640, Z = –1.020, $p > 0.05$), or passion for work (U = 6023, Z = –0.211, $p > 0.05$). The overall entrepreneurial mindset composite score did not differ significantly between groups (U = 5175.5, Z = –1.888, $p > 0.05$).

Table 6
Descriptive Statistics of Faculty Entrepreneurial Mindset and the Mann–Whitney U Test Results Regarding Entrepreneurship Course Study.

	Ent Studied	*N*	Mean Rank	Mean	*SD*	M-WU Test	Decision
Risk Taking	Yes	180	117.35	3.42	0.065	0.007(*U* = 6484.5;	Reject the null
	No	68	143.43	3.78	0.102	*Z* = -2.712)	hypothesis
Innovativeness	Yes	180	115.67	3.93	0.067	0.001(*U* = 4531;	Reject the null
	No	68	147.87	4.31	0.099	*Z* = -3.443)	hypothesis
Autonomy	Yes	180	123.86	3.56	0.075	0.811(*U* = 6005;	Retain the null
	No	68	126.19	3.60	0.109	Z = -.239)	hypothesis
Proactiveness	Yes	180	121.83	3.82	0.066	0.308(*U* = 5640;	Retain the null
	No	68	131.56	3.94	0.107	*Z* =-1.020)	hypothesis
Passion	Yes	180	123.96	3.84	0.064	0.833(*U* = 6023;	Retain the null
	No	68	125.93	3.9	0.084	*Z* = -.211)	hypothesis
Faculty Entrepreneurial Mindset	Yes	180	119.25	3.71	0.06	0.059(*U* = 5175.5;	Retain the null
	No	68	138.39	3.91	0.08	*Z* = -1.888)	hypothesis
	Total	248					

Entrepreneurship Workshops Participated in and Entrepreneurial Mindset

Table 7 shows the relationship between entrepreneurial mindset among faculty who participated in entrepreneurship workshops (n = 184) and those who had not (n = 64). There are statistically significant differences in all dimensions of entrepreneurial mindset: autonomy (U = 4636, Z = -2.655, p < .01), openness to novelty (U = 4140, Z = -3.862, p < .001), decision-making speed (U = 4500.5, Z = -3.007, p < .01), and passion for work (U = 4700, Z = -2.635, p < .01), except for risk-taking. Also, there is a significant relationship between entrepreneurial mindset and participation in entrepreneurship-related workshops. The overall entrepreneurial mindset composite score was significantly higher among faculty who had participated in workshops (M = 3.85) compared to those who had not (M = 3.53; U = 4389.5, Z = -3.055, p < .01).

Table 7
Descriptive Statistics of Faculty Entrepreneurial Mindset and the Mann–Whitney U Test Results Regarding Entrepreneurship Workshop Participation

	Ent Workshop Taken	*N*	Mean Rank	Mean	*SD*	M-WU Test	Decision
Risk Taking	Yes No	184 64	129.20 111.00	3.58 3.34	0.068 0.092	.064(*U* = 5024; *Z* = -1.855)	Retain the null hypothesis
Innovativeness	Yes No	184 64	134.00 97.19	4.15 3.69	0.06 0.113	.000(*U* = 4140; *Z* = -3.862)	Reject the null hypothesis
Autonomy	Yes No	184 64	131.30 104.94	3.65 3.33	0.07 0.11	.008(*U* = 4636; *Z* = -2.655)	Reject the null hypothesis
Proactiveness	Yes No	184 64	132.04 102.82	3.94 3.61	0.065 0.11	.003(*U* = 4500.5; *Z* =-3.007)	Reject the null hypothesis
Passion	Yes No	184 64	130.96 105.94	3.92 3.67	0.062 0.092	.008(*U* = 4700; *Z* = -2.635)	Reject the null hypothesis
Faculty Entrepreneurial Mindset	Yes No	184 64	132.64 101.09	3.85 3.53	0.06 0.09	.002(*U* = 4389.5; *Z* = -3.055)	Reject the null hypothesis
	Total	248					

Teaching Entrepreneurship Courses: Experience and Entrepreneurial Mindset

Table 8 shows whether faculty involved in the teaching of entrepreneurship-related courses have a different entrepreneurial mindset compared to those who do not teach entrepreneurship-related courses. The result showed that faculty who had taught entrepreneurship courses reported a significantly higher willingness to take risks to achieve real success (U = 4851.5, Z = -2.342, p = .019) and autonomy in working style (U = 4365, Z = -3.338, p = .001). Teaching entrepreneurship nurtures risk-taking and independence as fundamental aspects of the entrepreneurial mindset (Joensuu-Salo et al., 2020). There is no significant difference in perceptions regarding working on structured tasks (U = 5716.5, Z = -0.508, p = .612), decision-making process (U = 5147, Z = -1.726, p = .084), and passion for work (U = 5314.5, Z = -1.397, p = .162). This suggests that some personality-related traits, such as passion and way of doing structured tasks, are not influenced by teaching practices (Fatemi & Sazegar, 2016). The overall entrepreneurial mindset of faculty was significantly higher among those who taught entrepreneurship (U = 4730, Z = -2.469, p = .014), and it is statistically significant.

Table 8
Descriptive Statistics of Faculty Entrepreneurial Mindset and the Mann–Whitney U Test Results Regarding Teaching Entrepreneurship Courses Experience

	Ent Course Taught	*N*	Mean Rank	Mean	*SD*	M-WU Test	Decision
Risk Taking	Yes	183	130.49	3.60	0.065	.019(*U* = 4851.5; *Z* = -2.342)	Reject the null hypothesis
	No	65	107.64	3.29	0.11		
Innovativeness	Yes	183	125.76	4.04	0.067	.612(*U* = 5716.5; *Z* = -.508)	Retain the null hypothesis
	No	65	120.95	4.00	0.105		
Autonomy	Yes	183	133.15	3.69	0.073	.001(*U* = 4365; *Z* = -3.338)	Reject the null hypothesis
	No	65	100.15	3.23	0.109		
Proactiveness	Yes	183	128.87	3.91	0.065	.084(*U* = 5147; *Z* =-1.726)	Retain the null hypothesis
	No	65	112.18	3.69	0.11		
Passion	Yes	183	127.96	3.89	0.06	.162(*U* = 5314.5; *Z* = -1.397)	Retain the null hypothesis
	No	65	114.76	3.77	0.097		
Faculty Entrepreneurial Mindset	Yes	183	131.15	3.83	0.06	.014(*U* = 4730; *Z* = -2.469)	Reject the null hypothesis
	No	65	105.77	3.60	0.08		
	Total	248					

Teaching Level and Entrepreneurial Mindset

Table 9 shows the Kruskal–Wallis test results examining whether there were significant differences in the entrepreneurial mindset of faculty according to their teaching program level (Bachelor's, Master's, or both). The findings showed statistically significant differences across most measured dimensions of entrepreneurial mindset: risk-taking (χ^2 = 8.354, *df* = 2, *p* = .015), structured tasks (χ^2 = 23.297, df = 2, *p* = .000), autonomy in work (χ^2 = 17.020, *df* = 2, *p* = .000), and decision-making process (χ^2 = 8.591, *df* = 2, *p* = .014). However, there was no statistically significant difference in passion for work (χ^2 = 1.501, *df* = 2, *p* = .472). The aggregate entrepreneurial mindset score also differed significantly across teaching levels (χ^2 = 12.251, *df* = 2, *p* = .002). The mean scores indicate that faculty teaching in both programs (*M* = 3.83) and at the bachelor's level (*M* = 3.88) displayed stronger entrepreneurial mindset traits compared to those teaching exclusively at the master's level (*M* = 3.32).

Table 9
Descriptive Statistics of Faculty Entrepreneurial Mindset and the Mann–Whitney U Test Results Regarding Teaching Level

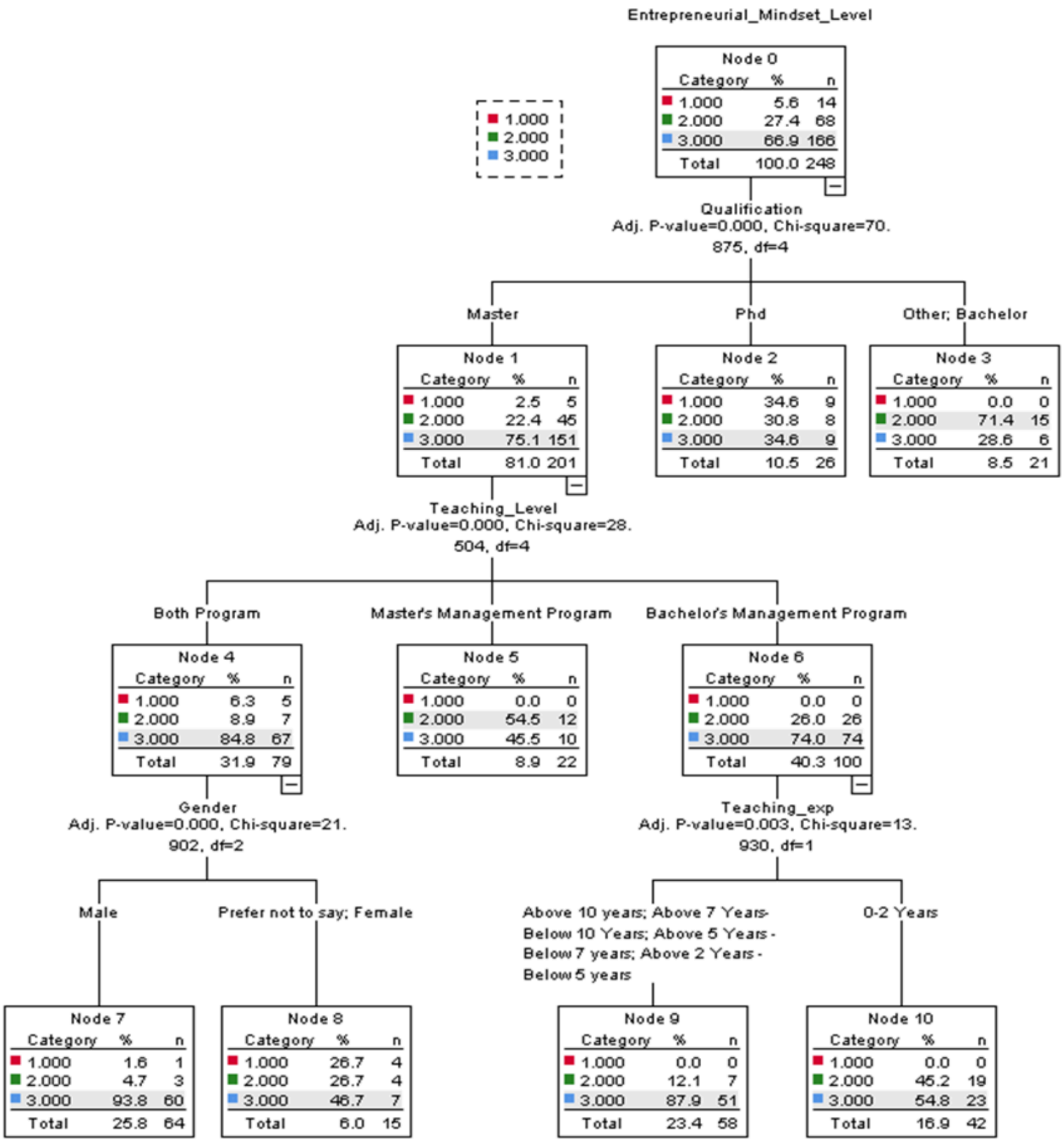
	Program Level	*N*	Mean Rank	Mean	*SD*	K-W Test	Decision
Risk Taking	Bachelor's	116	129.25	3.59	0.080	0.015	Reject the
	Master's	43	97.50	3.12	0.167	(χ^2 = 8.354;	null
	Both	89	131.35	3.62	0.077	*df* = 2)	hypothesis
Innovativeness	Bachelor's	116	138.35	4.27	0.06	0.000	Reject the
	Master's	43	81.99	3.37	0.173	(χ^2 = 23.297;	null
	Both	89	126.98	4.04	0.098	*df* = 2)	hypothesis
Autonomy	Bachelor's	116	130.47	3.68	0.087	0.000	Reject the
	Master's	43	85.66	2.98	0.168	(χ^2 = 17.020;	null
	Both	89	135.49	3.71	0.092	*df* = 2)	hypothesis
Proactiveness	Bachelor's	116	133.20	4.01	0.063	0.014	Reject the
	Master's	43	98.27	3.47	0.161	(χ^2 = 8.591;	null
	Both	89	125.83	3.84	0.103	*df* = 2)	hypothesis
Passion	Bachelor's	116	123.33	3.87	0.07	0.472	Retain the
	Master's	43	115.72	3.67	0.16	(χ^2 = 1.501;	null
	Both	89	130.26	3.93	0.08	*df* = 2)	hypothesis
Faculty	Bachelor's	116	129.39	3.88	0.05	0.002	Reject the
Entrepreneurial	Master's	43	90.34	3.32	0.15	(χ^2 = 12.251;	null
Mindset	Both	89	134.63	3.83	0.08	*df* = 2)	hypothesis
	Total	248					

Decision Tree Analysis

The decision tree analysis was performed using the chi-square automatic interaction detection (CHAID) method. As CHAID relies on chi-square tests, it does not assume normality and thus can be considered a distribution-free exploratory method (McHugh, 2013). In the CHAID procedure, the analysis selects the independent variable that shows the strongest relationship with the dependent variable at each step. Categories of the independent variable are grouped if their differences are not statistically significant. The dependent variable, entrepreneurial mindset, was recorded as a categorical variable, where entrepreneurial mindset intensity was coded as 1.00 through 2.49 as low, 2.50 through 3.49 as moderate, and 3.50 through 5.00 as high. It enhances the interpretability of CHAID results while maintaining consistency with the distribution and nature of the data. CHAID requires categorical dependent variables; thus, a transformation was necessary and methodologically appropriate.

A decision tree shown in Figure 2 was calculated in a 40/15 decision node. The CHAID model has a risk estimate of 0.286 (SE = 0.029), indicating that approximately 71.4% of cases in this node are correctly classified. The classification tree analysis revealed distinct patterns in the entrepreneurial mindset level of respondents (*N* = 248). At the overall level, 66.9% of respondents exhibited a high entrepreneurial mindset, 27.4% reported a medium level, and only 5.6% indicated a low level. The most significant predictor of entrepreneurial mindset was qualification (χ^2 = 70.875, p < 0.001). Master's degree holders (n = 201) demonstrated the strongest entrepreneurial orientation, with 75.1% categorized at the high level, whereas PhD holders (n = 26) displayed a more even distribution across low (34.6%), medium (30.8%), and high (34.6%) levels. Respondents with other or bachelor's qualifications (n = 21) were predominantly at the medium level (71.4%).

Figure 1
Decision Tree Analysis



The second classification criterion is the teaching program level, but only for the group that has a master's degree mindset ($\chi^2 = 28.504$, $p < 0.001$). Those teaching both bachelor's and master's programs (n = 79) had 84.8% in the high mindset group, compared to 74.0% among bachelor's-only teachers (n = 100) and 45.5% among master's-only teachers (n = 22).

The third classification criterion is gender, but only for the group of faculties that are involved in teaching both programs. Gender was significant ($\chi^2 = 21.902$, $p < 0.001$): 93.8% of males exhibited a high entrepreneurial mindset, compared with 46.7% of females/prefer not to say.

Another third classification criterion is teaching experience, but only for the faculty group who are involved in teaching bachelor's programs ($\chi^2 = 13.930$, $p = 0.003$). Respondents with more teaching experience (n = 58) reported a higher level of entrepreneurial mindset (87.9%), while less experienced teachers (n = 42) were split between medium (45.2%) and high (54.8%).

Discussion/Implications

In the emerging entrepreneurship literature, the study of the entrepreneurial mindset has gained growing consideration. Nonetheless, only a few studies have explored the role of demographic and entrepreneurial exposure in shaping faculty entrepreneurial mindset. This study is aimed at exploring what demographic factors and entrepreneurial experience affect the entrepreneurial mindset of the faculty, especially in the higher education sector.

The results show that gender plays a vital role in developing an entrepreneurial mindset. The results suggest that while entrepreneurial risk-taking, autonomy, and overall orientation are higher among male faculty, intrinsic motivation and decision-making have no significant difference between genders. These differences may be explained by gender-based variations in behavioral and psychological orientations. It confirms significant gender differences in overall entrepreneurial mindset, which is aligned with previous research (Ahmad, 2022; Cacija et al., 2023; Justus, 2021). While male faculty exhibit higher risk-taking, autonomy, and overall entrepreneurial mindset, intrinsic motivation and decision-making do not differ significantly across genders.

The findings of this study highlight that age does not play a significant role in the development of an entrepreneurial mindset. This result is consistent with Degefu and Verma's (2025) and Nguyen's (2018) research; however, it is important to note that the respondents' categories were different from those in this study. The result concludes that age plays an important role in shaping specific entrepreneurial traits, and entrepreneurial mindset is not uniformly influenced by age; rather, certain dimensions evolve depending on career stage, with mid-career faculty appearing more dynamic in terms of creativity, decision-making, and passion, while other foundational traits remain consistent over time.

The findings of this study further demonstrate that faculty teaching experiences influenced the risk-taking attitude, innovativeness, and passion towards the work; however, it does not have a significant role in defining the overall entrepreneurial mindset. The result indicates that faculty who are passionate about teaching will continue to teach for a longer period of time. The findings suggest that teaching experience does not have an influence on overall entrepreneurial mindset but shows different results across dimensions. The result indicates that there is low passion for teaching among the new faculty; the institution should bring programs to support it. For the mid-career faculty, the institution should be more focused on promoting risk-taking and passion development, and for the experienced faculty to take risks and promote innovation in teaching.

Furthermore, the analysis shows that academic qualification plays a vital role in shaping entrepreneurial mindset, with Master's degree holders consistently demonstrating stronger orientations across multiple dimensions. Faculty with a Master's degree consistently showed high entrepreneurial intention, which is very notable and significant for the institution while hiring faculty. The result shows that faculty with PhD degrees scored lower in entrepreneurial dimensions and overall entrepreneurial mindset; this result is significant as it indicates that faculty with doctoral degrees are more focused on systems and processes, have depth of expertise, but not necessarily entrepreneurial agility. This result is consistent with the age group and teaching experience findings. Faculty with higher degrees, more teaching experience, and higher age groups consistently show a lower entrepreneurial mindset. This indicates that institutions should develop relevant development programs and workshops to keep them innovative in the workplace.

The result shows that, across all dimensions and the entrepreneurial mindset composite score, faculty who did not study entrepreneurship-related courses show higher scores than those who have studied entrepreneurship-related subjects. While entrepreneurship courses are designed to foster entrepreneurial qualities, the result showed that participants reported lower levels of entrepreneurial mindset. Miço and Cungu (2023) indicated that while entrepreneurship education introduces entrepreneurship-related knowledge, risk-taking strategies, and concepts of entrepreneurship, it might create a risk-aversion mindset rather than innovation, either because of teaching strategies and curriculum design and offering (Deng & Wang, 2023), or personal traits (Pham et al., 2023). The results signify that entrepreneurship curricula and their offering strategies need to be revisited. The curriculum should promote innovation and actively encourage risk orientation and openness to novelty to improve the overall entrepreneurial mindset.

The findings show that the entrepreneurship workshop has a direct influence on how individuals think about bringing innovation, supporting the view that entrepreneurial learning environments encourage proactive, opportunity-oriented thinking. This finding indicates that entrepreneurship workshops provide a valuable platform for enhancing entrepreneurial attitude and mindset (Pham et al., 2023). This finding suggests that exposure to entrepreneurship workshops foster greater flexibility and a preference for innovation, improving proactiveness (Al-Awlaqi et al., 2021; Morris et al., 2023). Overall, entrepreneurship workshops have a positive and significant impact on most aspects of the entrepreneurial mindset besides risk-taking. Thus, institutions should provide an opportunity for the faculty to participate in entrepreneurship-related workshops regularly.

The findings of this study further demonstrate the reinforcing role of teaching entrepreneurship in cultivating broader entrepreneurial attitudes and orientations. The faculty who taught entrepreneurship-related courses practiced entrepreneurial traits and focused on developing those traits. Their mindset emphasizes creativity, flexibility, and independence in problem-solving, which is the core of entrepreneurship (Neck & Corbett, 2018). These results imply that entrepreneurship teaching not only benefits students but also contributes to shaping the entrepreneurial mindset of faculty themselves. The overall entrepreneurial mindset composite score was significantly higher among faculty who had taught entrepreneurship-related courses ($M = 3.83$) compared to those who had not ($M = 3.60$). Thus, it also signifies that teaching entrepreneurship helps faculty to develop their own entrepreneurial mindset.

The result confirmed that teaching level has an important influence on entrepreneurial mindset. Faculty at the bachelor’s and dual-program levels may be more exposed to practical, hands-on, and innovation-driven teaching approaches, which could reinforce entrepreneurial traits. In contrast, faculty teaching at the master’s level may be more engaged with research, theoretical frameworks, and structured pedagogy, which might limit entrepreneurial expression. This aligns with prior research, which highlights that an entrepreneurial mindset is strengthened when faculty are involved in practice-oriented teaching and active engagement with learners (Lynch & Booking, 2023). The curriculum and teaching strategies across different programs influence faculty mindset and the way of delivering classroom instruction (Gningue et al., 2024). The level of the program and teaching strategies need to be differentiated; thus, faculty exercise different levels of entrepreneurial mindset.

Further, the above results were confirmed through the decision tree analysis. The findings suggest that an entrepreneurial mindset is strongly associated with academic qualification, teaching level, gender, and teaching experience. These results indicate that faculty qualification and teaching level are the most consistent predictors across all dimensions of entrepreneurial mindset. Workshop participation also significantly shaped several dimensions, while gender and age had selective but notable effects. In contrast, teaching experience and entrepreneurship courses studied influenced specific dimensions but did not affect the overall mindset. These findings highlight that faculty entrepreneurial mindset is shaped by a combination of personal attributes and professional engagement.

This study has theoretical and practical implications for higher education institutions and faculty. This research applied demographic variables and entrepreneurial exposure, with the aim of examining how traits influenced entrepreneurial mindset. This is a limited research area in higher education, especially among the faculty, so it provided a theoretical contribution and developed a theoretical understanding for future research. Further, this paper has applied the CHAID decision tree analysis to explore the relationship, which has been limited in the higher education literature in developing countries like Nepal.

This study shows that faculty qualification and teaching level have influenced the overall entrepreneurial mindset. This suggests that educational institutions need to create an opportunity for the faculty to engage in entrepreneurship-related workshops and training. They should integrate applied, practice-oriented methods into both faculty training and curriculum design. Although gender difference is not a significant overall entrepreneurial mindset, female faculty show a relatively low entrepreneurial mindset, thus emphasizing the need for inclusive institutional policies that encourage risk-taking and autonomy among female faculty. Faculty should attend entrepreneurship-related workshops and training.

The government has a vital role to play in fostering an entrepreneurial mindset among the faculty. Like they have a program related to entrepreneurship for the students, they should develop a similar program that provides an opportunity for the faculty to participate and learn. These programs can be initiated as part of a faculty development plan. By nurturing a culture of an innovative mindset, it can contribute significantly to the development of an entrepreneurial mindset.

Limitation

This study has adopted a five-dimensional entrepreneurial mindset, and those dimensions were measured through a single measure. In future research, multiple items should be used to measure each dimension to capture the construct more comprehensively. This study applied a cross-sectional design to collect data from the higher education faculties; thus, not able to explore whether the exposure to entrepreneurial-related activities actually develops an entrepreneurial mindset or not. Longitudinal research could be conducted to show the impact. Further, the research has been conducted among the faculty in Nepal; depending upon the context, it might be different, so it needs to be generalized with caution. The study examined demographic and entrepreneurial exposure with five key dimensions of entrepreneurial mindset, but did not explore broader institutional factors, such as those that may shape faculty attitudes and behaviors. Future studies could consider those individual and organizational-level factors to capture deeper insights into how the entrepreneurial mindset develops and is expressed in academic contexts.

Conclusion

This study examined the relationship between higher education institution faculty demographics and entrepreneurial exposure with entrepreneurial mindset, i.e., risk-taking, innovativeness, autonomy, proactiveness, and passion. The results showed that the faculty's entrepreneurial mindset is positive and particularly strong in innovativeness, proactiveness, and passion, whereas the risk-taking attitude was low. These reflect that the faculties are very cautious to take risks in higher education initiatives. The academic qualifications of the faculty are significant and do influence how faculty think and tend to act. Further, teaching level, gender, and experience have played a vital role in shaping the entrepreneurial mindset among the faculty. Faculty who had engaged in entrepreneurship workshops or taught entrepreneurship courses also showed higher entrepreneurial orientation, suggesting that applied and practice-based experiences reinforce entrepreneurial traits.

These findings contribute to the growing body of literature on entrepreneurial mindset in academia and highlight the dynamic and multidimensional nature of the entrepreneurial mindset among faculty. The study underlines the importance of designing policies and interventions that encourage innovative thinking and develop faculty who are better positioned to model and cultivate entrepreneurial skills in students, which contributes towards an entrepreneurship culture in the educational sector.

References

Abidi, O., Nimer, K., Bani-Mustafa, A., & Toglaw, S. (2022). Relationship between faculty characteristics and their entrepreneurial orientation in higher education institutions in Kuwait. *Journal of Innovation and Entrepreneurship, 11*(1), 12. https://doi.org/10.1186/s13731-022-00206-7

Abo-Khalil, A. G. (2024). Integrating sustainability into higher education: Challenges and opportunities for universities worldwide. *10*(9), e29946. https://doi.org/10.1016/j.heliyon.2024.e29946

Adachi, T., & Hisada, T. (2017). Gender differences in entrepreneurship and intrapreneurship: An empirical analysis. *Small Business Economics, 48*, 447–486. https://doi.org/10.1007/s11187-016-9793-y

Ajzen, I. (2002). Perceived behavioral control, self-efficacy, locus of control, and the theory of planned behavior. *Journal of Applied Social Psychology, 32*(4), 665–683. https://doi.org/10.1111/j.1559-1816.2002.tb00236.x

Al-Awlaqi, M. A., Aamer, A. M., & Habtoor, N. (2021). The effect of entrepreneurship training on entrepreneurial orientation: Evidence from a regression discontinuity design on micro-sized businesses. *The International Journal of Management Education, 19*(1), 10026. https://doi.org/10.1016/j.ijme.2018.11.003

Alhosseiny, H., & Ahmad, M. U. (2022). Faculty traits and learning in entrepreneurship courses: Evidence from a moderation analysis. *Journal of Entrepreneurship Education, 26*(S1), 1–9. https://ssrn.com/abstract=4288654

Al-Lawati, E. H., Abdul Kohar, U. H., & Shahrin Suleiman, E. (2022). Entrepreneurial culture in educational institutions: A scoping review. *Cogent Business & Management, 9*(1), 3-28 https://doi.org/10.1080/23311975.2021.1997237

Amaley, J. A. (2014). The changing role of higher education: Learning to deal with wicked problems. *Journal of Higher Education Outreach and Engagement, 18*(3), 7–22. https://files.eric.ed.gov/fulltext/EJ1043282.pdf

Bohlmann, C., Rauch, A., & Zacher, H. (2017). A lifespan perspective on entrepreneurship: Perceived opportunities and skills explain the negative association between age and entrepreneurial activity. *Frontiers in Psychology, 8*, 2015. https://doi.org/10.3389/fpsyg.2017.02015

Bosman, L., & Fernhaber, S. (2018). Defining the entrepreneurial mindset. In *Teaching the entrepreneurial mindset to engineers* (pp. 7–14). Springer. https://doi.org/10.1007/978-3-319-61412-0_2

Bosman, L., & Fernhaber, S. (2021). Introduction to the entrepreneurial mindset teaching blueprint. In *Teaching the entrepreneurial mindset across the university* (pp. 33–46). Springer. https://doi.org/10.1007/978-3-030-79050-9_4

Brush, C., Wraae, B., & Nikou, S. (2024). Understanding influences on the entrepreneurship educator role identity. *Education + Training, 66*(10), 1–28. https://doi.org/10.1108/ET-01-2022-0007

Cacija, L. N., Lovrincevic, M., & Bilic, I. (2023). The role of demographic factors and prior entrepreneurial exposure in shaping the entrepreneurial intentions of young adults: The case of Croatia. *Sustainability*, *15*(6), 5151. https://doi.org/10.3390/su15065151

Chaudhary, R. (2017). Demographic factors, personality and entrepreneurial inclination: A study among Indian university students. *Education + Training, 59*(2), 171–187. https://doi.org/10.1108/ET-02-2016-0024

Daspit, J. J., Fox, C., & Findley, S. K. (2023). Entrepreneurial mindset: An integrated definition, a review of current insights, and directions for future research. *Journal of Small Business Management, 61*(1), 12–44. https://doi.org/10.1080/00472778.2021.1907583

Davis, M. H., Hall, J. A., & Mayer, P. S. (2016). Developing a new measure of entrepreneurial mindset: Reliability, validity, and implications for practitioners. *Consulting Psychology Journal: Practice and Research*, *68*(1), 21. https://doi.org/10.1037/cpb0000045

De la Gala-Velásquez, B., Hurtado-Palomino, A., Monrroy-Villena, A. A., & Gomez-Villegas, O. I. (2024). Roots of the entrepreneurial mindset in university students. *The International Journal of Management Education, 22*(3), 101049. https://doi.org/10.1016/j.ijme.2024.101049

Degefu, M. E., & Verma, P. (2025). How do demographic variables influence the entrepreneurial mindsets of students in Ethiopia? Exploring implications for improving entrepreneurial education. *Innovations in Education and Teaching International*, 1–16. https://doi.org/10.1080/14703297.2025.2483377

Della Piana, B., Bayraktar, S., & Jimenez, A. (2024). Entrepreneurial mindsets across cultures. In A. Botti & R. Parente (Eds.), Humane entrepreneurship and innovation: An alternative way to promote sustainable development (pp. 15–192). https://doi.org/10.1108/978-1-83797-374-320241010

Deng, W., & Wang, J. (2023). The effect of entrepreneurship education on the entrepreneurial intention of different college students: Gender, household registration, school type, and poverty status. *PLOS ONE, 18*(7), e0288825. https://doi.org/10.1371/journal.pone.0288825

Dinh, A., Oberrauch, L., & Dewalt, S. (2022). What's in a mindset? Exploring the entrepreneurial mindset. *Journal of Entrepreneurship Education, 25*(4), 1–24. https://www.abacademies.org/articles/whats-in-a-mindset-exploring-the-entrepreneurial-mindset-15034.html#r17

Fatemi, M. A., & Sazegar, Z. (2016). The relationship between teachers' personality traits and doing action research. *Journal of Applied Linguistics and Language Research, 3*(1), 144–154. https://oaji.net/articles/2014/1573-1420485745.pdf

Fernández-Cruz, F. J., & Rodríguez-Legendre, F. (2021). The innovation competence profile of teachers in higher education institutions. *Innovations in Education and Teaching International, 59*(6), 634–645. https://doi.org/10.1080/14703297.2021.1905031

Gibb, A. (2003). In pursuit of a new 'enterprise' and 'entrepreneurship' paradigm for learning: Creative destruction, new values, new ways of doing things and new combinations of knowledge. *International Journal of Management Reviews, 5*(3–4), 233–269. https://doi.org/10.1111/1468-2370.00086

Gningue, S. M., Qian, G., Robinson, J. M., & Erbilgin, E. (2024). Impacts of teachers' mindsets on their ways of teaching students in high needs schools. *SAGE Open, 14*(2), 1–13.https://doi.org/10.1177/21582440241259355

Gorlewicz, J. L., & Jayaram, S. (2019). Instilling curiosity, connections, and creating value in entrepreneurial minded engineering: Concepts for a course sequence in dynamics and controls. *Entrepreneurship Education and Pedagogy*, *3*(1), 60-85. https://doi.org/10.1177/2515127419879469

Gunawan, A. F. (2024). The impact of entrepreneurial characteristics and competencies on business performance in the creative industry in Indonesia. *Asia Pacific Journal of Innovation and Entrepreneurship,* *18*(3), 300–317. https://doi.org/10.1108/APJIE-09-2023-0172

Hahn, D., Minola, T., Van Gils, A., & Huybrechts, J. (2017). Entrepreneurial education and learning at universities: Exploring multilevel contingencies. *Entrepreneurship & Regional Development,* *29*(9–10), 945–974. https://doi.org/10.1080/08985626.2017.1376542

Hayter, C. S., Nelson, A. J., Zayed, S., & O'Connor, A. C. (2018). Conceptualizing academic entrepreneurship ecosystems: A review, analysis and extension of the literature. *The Journal of Technology Transfer,* *43*(4), 1039–1082. https://doi.org/10.1007/s10961-018-9657-5

Hölzner, H. M., & Halberstadt, J. (2023). Challenge-based learning: How to support the development of an entrepreneurial mindset. In J. Halberstadt, A. Alcorta de Bronstein, J. Greyling, & S. Bissett (Eds.), *Transforming entrepreneurship education* (pp. 23-36). Springer. https://doi.org/10.1007/978-3-031-11578-3_2

Imran, T., Ahmed, R. R., Streimikiene, D., Soomro, R. H., Parmar, V., & Vveinhardt, J. (2019). Assessment of entrepreneurial traits and small-firm performance with entrepreneurial orientation as a mediating factor. *Sustainability,* *11*(19), 5301. https://doi.org/10.3390/su11195301

Joensuu-Salo, S., Peltonen, K., Hämäläinen, M., Oikkonen, E., & Raappana, A. (2020). Entrepreneurial teachers do make a difference – Or do they? *Industry and Higher Education,* *35*(4), 536–546. https://doi.org/10.1177/0950422220983236

Jovicic Vukovic, A., Josanov-Vrgovic, I., Jovin, S., & Papic-Blagojevic, N. (2020). Socio-demographic characteristics and students' entrepreneurial intentions. *Stanovništvo,* *58*(2), 57–75. https://doi.org/10.2298/STNV200423007J

Jung, E., & Lee, Y. (2020). College students' entrepreneurial mindset: Educational experiences override gender and major. *Sustainability,* *12*(19), 8272. https://doi.org/10.3390/su12198272

Justus, X. (2021). Support for start-up entrepreneurs and current trends strengthening the competitiveness of business entities. *SHS Web of Conferences*, *90*, 02005. https://doi.org/10.1051/shsconf/20219002005

Kaya, S., & Yuksel, D. (2022). Teacher mindset and grit: How do they change by teacher training, gender, and subject taught? *Participatory Educational Research,* *9*(6), 418–435. http://dx.doi.org/10.17275/per.22.146.9.6

Kearney, C., & Meynhardt, T. (2016). Directing corporate entrepreneurship strategy in the public sector to public value: Antecedents, components, and outcomes. *International Public Management Journal, 19*(4), 543–572. https://doi.org/10.1080/10967494.2016.1160013

Kerr, S. P., Kerr, W. R., & Xu, T. (2017). *Personality traits of entrepreneurs: A review of recent literature* (Working Paper No. 18-047). Harvard Business School. https://www.hbs.edu/ris/Publication%20Files/18-047_b0074a64-5428-479b-8c83-16f2a0e97eb6.pdf

Kuratko, D. F., Fisher, G., & Audretsch, D. B. (2021). Unraveling the entrepreneurial mindset. *Small Business Economics, 57*(4), 1681–1691. https://doi.org/10.1007/s11187-020-00372-6

Liang, J., Wang, H., & Lazear, E. P. (2014). *Demographics and entrepreneurship* (Working Paper No. 20506). National Bureau of Economic Research. https://www.nber.org/system/files/working_papers/w20506/w20506.pdf

Lynch, A. C., & Booking, G. (2023). Cultivating curiosity: Instilling an entrepreneurial mindset with project-based learning. In *ASEE North Midwest Section Annual Conference 2023 Publications*. South Dakota State University. https://openprairie.sdstate.edu

Mathisen, J. E., & Arnulf, J. K. (2013). Competing mindsets in entrepreneurship: The cost of doubt. *The International Journal of Management Education, 11*(3), 132–141. https://doi.org/10.1016/j.ijme.2013.03.003

McHugh, M. L. (2013). The chi-square test of independence. *Biochemia Medica, 23*(2), 143–149. https://doi.org/10.11613/bm.2013.018

Meilani, A., & Ginting, G. (2018). The variables and dimensions of entrepreneurial orientation perceived by lecturers of higher education institutions. *Review of Integrative Business and Economics Research, 7*, 404-410. https://www.sibresearch.org/uploads/3/4/0/9/34097180/riber_7-s2_uk18-112_404-410.pdf

Miço, H., & Cungu, J. (2023). Entrepreneurship education, a challenging learning process towards entrepreneurial competence in education. *Administrative Sciences, 13*(1), 22. https://doi.org/10.3390/admsci13010022

Morris, S., Carlos, C., Kistruck, G. M., Lount, R. B., Jr., & Thomas, T. E. (2023). The impact of growth mindset training on entrepreneurial action among necessity entrepreneurs: Evidence from a randomized control trial. *Strategic Entrepreneurship Journal, 17*(4), 1002–1032. https://doi.org/10.1002/sej.1472

Muange, R. M., & Kiptoo, N. W. (2020). Effect of workforce ethnic diversity and education background diversity on employee performance in selected universities in Kenya. *International Journal of Innovative Science and Research Technology, 5*(7), 1096–1103. https://doi.org/10.38124/IJISRT20JUL728

Muhammed, M., & Henry, M. (2024). Entrepreneurial mindset and opportunity identification: A case study of youth in Makerere University. *Metropolitan Journal of Business & Economics, 3*(10), 370–385.

Nabi, G., Liñán, F., Fayolle, A., Krueger, N., & Walmsley, A. (2017). The impact of entrepreneurship education in higher education: A systematic review and research agenda. *Academy of Management Learning & Education, 16*(2), 277–299. https://www.jstor.org/stable/26400192

Nadelson, L. S., Palmer, A. D. N., Benton, T., Basnet, R., Bissonnette, M., Cantwell, L., Jouflas, G., Elliott, E., Fromm, M., & Lanci, S. (2018). Developing next generation of innovators: Teaching entrepreneurial mindset elements across disciplines. *International Journal of Higher Education, 7*(5), 114–128. https://doi.org/10.5430/ijhe.v7n5p114

Najev Čacija, L., Lovrinčević, M., & Bilić, I. (2023). The role of demographic factors and prior entrepreneurial exposure in shaping the entrepreneurial intentions of young adults: The case of Croatia. *Sustainability, 15*(6), 5151. https://doi.org/10.3390/su15065151

Nakamura, J., & Csikszentmihalyi, M. (2004). Engagement in a profession: The case of undergraduate teaching. *Journal of the American Academy of Arts & Sciences, Summer 2005*, 60–67. https://doi.org/10.1162/0011526054622051

Neck, H. M., & Corbett, A. C. (2018). The scholarship of teaching and learning entrepreneurship. *Entrepreneurship Education and Pedagogy, 1*(1), 8–41. https://doi.org/10.1177/2515127417737286

Neergård, G.-B., & Roald, G. M. (2025). Competent to teach? Educators' perceptions of entrepreneurship. *International Journal of Entrepreneurial Behavior & Research, 31*(8), 2027–2048. https://doi.org/10.1108/IJEBR-07-2023-0712

Nguyen, C. (2018). Demographic factors, family background and prior self-employment on entrepreneurial intention—Vietnamese business students are different: Why? *Journal of Global Entrepreneurship Research, 8*, 10. https://doi.org/10.1186/s40497-018-0097-3

Nor, A. I., Mohamed, F. S., Barre, M. M., & Hussein, M. A. (2025). The role of higher education institutions in promoting entrepreneurship development. *Cogent Business & Management, 12*(1). 2523417. https://doi.org/10.1080/23311975.2025.2523417

Oestreich, M. (2023). Entrepreneurial mind-set: Cultivating traits for business triumph. *Journal of Research in International Business and Management*, *10*, 1-2.

Ostojić, M., & Leko Šimić, M. (2021). Students' perceptions of public vs. private higher education institution brand value in Croatia. *Sustainability, 13*(17), 9767. https://doi.org/10.3390/su13179767

Overwien, A., Jahnke, L., & Leker, J. (2024). Can entrepreneurship education activities promote students' entrepreneurial intention? *The International Journal of Management Education, 22*(1), 100928. https://doi.org/10.1016/j.ijme.2023.100928

Ozyilmaz, A. (2011). The effects of demographic characteristics on entrepreneurial intention in the pre-venture stage of entrepreneurship. *International Journal of Entrepreneurship and Small Business, 14*(3), 406–424. https://ideas.repec.org/a/ids/ijesbu/v14y2011i3p406-424.html

Paray, Z. A., & Kumar, S. (2020). Does entrepreneurship education influence entrepreneurial intention among students in HEIs? The role of age, gender and degree background. *Journal of International Education in Business, 13*(1), 55–72. https://doi.org/10.1108/JIEB-02-2019-0009

Pham, M., Nguyen, A. T. T., Tran, D. T., & others. (2023). The impact of entrepreneurship knowledge on students' e-entrepreneurial intention formation and the moderating role of technological innovativeness. *Journal of Innovation and Entrepreneurship, 12*, 80. https://doi.org/10.1186/s13731-023-00351-7

Pinto, P., Pallikkara, V., Pinto, S., & Hawaldar, I. T. (2024). Unveiling the entrepreneurial mindset: Exploring orientation and intentions among students of prominent engineering disciplines. *Journal of Innovation and Entrepreneurship*, *13*(1). 33. https://doi.org/10.1186/s13731-024-00390-8

Purohit, S., & Dutt, A. (2024). Pedagogical innovations in management education in the 21st century: A review and research agenda. *The International Journal of Management Education, 22*(2), 100976. https://doi.org/10.1016/j.ijme.2024.100976

Quan, X. (2012). Prior experience, social network, and levels of entrepreneurial intentions. *Management Research Review, 35*(10), 945–957. https://doi.org/10.1108/01409171211272679

Reynolds, P. D., Gartner, W. B., Greene, P. G., Cox, L. W., & Carter, N. M. (2002). *The entrepreneur next door: Characteristics of individuals starting companies in America: An executive summary of the Panel Study of Entrepreneurial Dynamics*. SSRN. https://doi.org/10.2139/ssrn.1262320

Robinson, P. B., & Gough, V. (2020). The right stuff: Defining and influencing the entrepreneurial mindset. *Journal of Entrepreneurship Education, 23*(2), 1–16. https://www.abacademies.org/articles/the-right-stuff-defining-and-influenceing-the-entrepreneurial-mindset-9044.html

Rodrigues, A. L. (2023). Entrepreneurship education pedagogical approaches in higher education. *Education Sciences, 13*(9), 940. https://doi.org/10.3390/educsci13090940

Rodrigues, R. G., Ferreira, J. J., & Felgueira, T. (2019). Entrepreneurial academics: A taxonomy with latent profile analysis. *Management Decision, 57*(12), 3346–3363. https://doi.org/10.1108/MD-10-2018-1157

Rossol-Allison, P. M., & Beyers, N. J. A. (2011). *The role of full-time and part-time faculty in student learning outcomes.* AIR 2011 Forum, Toronto, Ontario, Canada. https://files.eric.ed.gov/fulltext/ED531726.pdf

Salmony, F. U., & Kanbach, D. K. (2022). Personality trait differences across types of entrepreneurs: A systematic literature review. *Review of Managerial Science, 16*(3), 713–749. https://doi.org/10.1007/s11846-021-00466-9

Samsami, M. El Kolaly, H. González-Pernía, J. & Boutaleb, F. (2024). Gender roles shaping the entrepreneurial mindset: embedded in the entrepreneurial ecosystem and impacted by the pandemic. *European Journal of International Management, 22*(4), 551–575. https://doi.org/10.1504/EJIM.2024.137353

Santos, S. C., Caetano, A., Spagnoli, P., Costa, S. F., Neumeyer, X., & Wegner, D. (2017). Predictors of entrepreneurial activity before and during the European economic crisis. *International Entrepreneurship and Management Journal, 13*(4), 1263–1288. https://doi.org/10.1007/s11365-017-0453-8

Sarmah, A., Saikia, B., & Tripathi, D. (2022). Does entrepreneur gender matter for entrepreneurial motivation: Answers from micro, small and medium enterprises (MSMEs) of Assam. *Journal of International Women's Studies, 23*(5), 20–40. https://vc.bridgew.edu/jiws/vol23/iss5/3/

Sharma, V., & Ahmad, N. (2023). Role of demographics, entrepreneurship education and entrepreneurial social background in entrepreneurial intention of Indian business students. *EPRA International Journal of Economic and Business Review, 11*(12). https://doi.org/10.36713/epra15214

Shetty, G. S., Baliga, V., & Thomas Gil, M. (2024). Impact of entrepreneurial mindset and motivation on business performance: Deciphering the effects of entrepreneurship development program (EDPs) on trainees. *Cogent Business & Management, 11*(1), 2314733.https://doi.org/10.1080/23311975.2024.2314733

Shian, V. C. M., Ayob, N. B., Luva, R. H., Tehseen, S., Chong, S. M., Haider, S. A., & Yusof, M. (2022). Impact of personal characteristics on intrapreneurs' behaviours. *International Journal of Entrepreneurship, 26*(4), 1–15. https://www.abacademies.org/articles/impact-of-personal-characteristics-on-intrapreneurs-behaviours.pdf

Smith, R. M., Sardeshmukh, S. R., & Combs, G. M. (2016). Understanding gender, creativity, and entrepreneurial intentions. *Education + Training, 58*(3), 263–282. https://doi.org/10.1108/ET-06-2015-0044

Srivastava, A. (2025). Understanding entrepreneurial mindset in young adults: A study of personal traits, gender and regional influences. *Journal of Management and Social Research, 2*(5), 404–410. https://doi.org/10.61336/jmsr/25-05-46

Syed, R. T., Singh, D., Ahmad, N., & Butt, I. (2024). Age and entrepreneurship: Mapping the scientific coverage and future research directions. *International Entrepreneurship and Management Journal, 20*(2), 1451–1486. https://doi.org/10.1007/s11365-024-00964-8

Tasman, A., Patrisia, D., & Yanuarta, R. E. R. (2023). Demographic characteristics and business performance: Evidence in women entrepreneurs. In *Advances in Economics, Business and Management Research* (pp. 312–318). Proceedings of the Ninth Padang International Conference on Economics Education, Economics, Business and Management, Accounting and Entrepreneurship (PICEEBA 2022). https://doi.org/10.2991/978-94-6463-158-6_28

Wardana, L. W., Narmaditya, B. S., Wibowo, A., Mahendra, A. M., Wibowo, N. A., Harwida, G., & Rohman, A. N. (2020). The impact of entrepreneurship education and students' entrepreneurial mindset: The mediating role of attitude and self-efficacy. *Heliyon, 6*(9), e04922. https://doi.org/10.1016/j.heliyon.2020.e04922

Westover, J. H. (2025). Faculty entrepreneurship: Transforming academic expertise in the evolving higher education landscape. *Preprints*, 2025080510. https://doi.org/10.20944/preprints202508.0510.v1

Zulkifli, N. A., Suhairom, N., Abd Wahid, N. H., & Saipudin, N. A. (2025). Fostering entrepreneurial mindsets in teacher trainees: A study on entrepreneurship education for future educators. *Education*, 4371–4390. https://dx.doi.org/10.47772/IJRISS.2025.90400313

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