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Original Article

A Review of Human Factors in AI-Powered Underwriting Systems: Trust, Cognitive Load, and Decision Quality

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Abstract: *Human factors significantly affect the productivity of AI-related underwriting systems, with trust, cognitive load, and quality of decision being the leading factors. The implementation of AI has made the data collection process automatic, improved the decision-making accuracy, and opened up avenues for sophisticated risk assessment. The insights that AI can provide from large amounts of unprocessed data cannot be compared to the human skills for understanding the context, making good judgment, and doing personal customer interactions, which are still indispensable. The ability to provide user-friendly interfaces, clear outputs, and adjustable processes diminishes the mental effort and accelerates the decision-making process, thus nurturing human-machine collaboration effectively. The inclusion of Cognitive Load Theory and Need for Cognition makes it possible for AI systems to adapt to users of different skill levels, hence bettering the users' understanding and trust. The uses of robot-advisory, fraud detection, personalized recommendations, and algorithmic trading are good examples of how interpretability and accountability can be integrated into the AI systems. Nevertheless, these improvements come with issues such as invasion of privacy of data, absence of governing laws, difficulties in merging systems, moral dilemmas, and bias in algorithms. Solving these problems will ensure that AI-powered underwriting will always be accurate, quick, and ethically sound. In the end, the trust, fairness, and performance that lasts will be the result of the AI systems being designed to support human thinking rather than to take over.*

Keywords: *AI-Powered Underwriting, Human–AI Collaboration, Cognitive Load, Trust and Decision Quality, Explainable AI (XAI), Financial Services, Risk Assessment.*

I. INTRODUCTION

AI-powered systems' success and acceptance are very much connected with the human factor. The human factor is a crucial one, however, and the underwriters are the key players who interpret, validate, and act upon the AI-generated insights by mediating between data-driven algorithms and strategic business outcomes [1]. The problems that have surfaced in this area are the result of three aspects of cognitive and psychological processes which are the main determinants of human decision-making's efficiency. Human-AI collaboration research has pointed out that user confidence, transparency, model output interpretability, and cognitive load are the most important factors in defining AI-assisted decision performance [2]. Similarly, the cognitive system's overload stemming from a complicated AI interface design or source overflow can result in wrong judgments and low confidence in decisions.

Human factors interplay like the trust calibration, the cognitive load management, and the decision quality are greatly significant in AI-powered underwriting and they form the basis of the whole approach to making systems that are both intelligent and friendly to humans. Trust is very crucial in monetary terms especially in the systems of underwriting and advisory. Financial decision-making is a risky workplace environment that places trust at the centre of human-AI interaction and makes feedback visible and quantifiable. [3]. It is in this context that it becomes easy to analyse the issue of algorithmic appreciation, the issue of the gap in expertise and the issue of delayed feedback conditions, which have a significant influence on the dynamics of trust [4][5]. Also, financial literacy and cognitive ability may moderate these dynamics by affecting users' ability to interpret AI explanations and assess the reliability of performance.

Trust is the key factor in underwriting because it determines a user's level of acceptance and the quality of decision-making. The confidence in AI is a subject of research across many fields, but its conceptualisation remains disjointed due to the variety of AI systems and areas. [6]. Cognitive trust, which is based on the perceptions of competence and reliability, develops based on the accumulated knowledge and regular feedback on performance. Transparency, interpretability, and accountability should be closely applied to calibration strategies in underwriting decisions that entail complex risk profiles and policy data interpreted by algorithms that require trust.

The incorporation of Artificial Intelligence (AI) into the underwriting process has dramatically changed the situation of financial and insurance-related decision-making. In the past, human specialist knowledge, gut feeling and experience were the main factors in underwriting risk assessment, eligibility determination and setting prices fairly. On the contrary, AI, along with data-driven approaches such as natural language processing (NLP) [7], analytics, and predictive modelling, has resulted in underwriting that constitutes an intelligent, data-driven system capable of processing large data volumes, conducting risk assessments automatically, and even more accurately and efficiently regarding operation power and decision making [8][9]. Nonetheless, the human element is utterly required. AI systems pose difficulties primarily concerning human perception, confidence, and collaboration with machines in choices, which, together with the quality and ethical acceptability of automated underwriting, are the main factors.

A. Organization of the Paper

Section II delves into the human elements in AI-assisted decision systems, prioritizing the combination of human skill and machine support. Section III discusses the cognitive burden in AI-supported decision-making processes, focusing on methods to reduce mental fatigue through design. Section IV examines the relationship between trust and decision quality in human-AI partnerships, highlighting the contribution of generative AI in finance. Section V wraps up the literature analysis and presents the principal conclusions regarding AI-powered underwriting systems. Ultimately, Section VI closes with advice and outlines future research areas for the ethical and explainable use of AI.

II. HUMAN FACTORS IN AI-DRIVEN DECISION SYSTEMS

Artificial Intelligence-powered decision-making systems have greatly transformed the underwriting procedure to such a degree that they have played a key role in gathering standardized data, making the process more precise, quicker, and uniform and at the same time, facilitating better risk evaluation through the data. Even though AI is capable of processing enormous quantities of data in no time and even spotting the risk trends that are not visible, human intervention is still very important. The underwriters not only have to understand the AI's output but also to build trust independent of AI and manage their mental effort [10][11]. The creation of AI tools with straightforward interfaces and easily comprehensible insights is an important aspect of the retention of beneficial human-machine cooperation, which consequently leads to underwriting decisions that are faster, more accurate, and more equitable.

A. Understanding AI in Insurance Underwriting

The inclusion of smart agents, or just AI, has greatly transformed the insurance underwriting procedure, turning it into one that is more automated, accurate, and based on data for decision-making. The transformation speeds up the process and also enhances the quality of the decisions taken. AI can handle technology-driven, repetitive tasks, completing them within minutes for hard-copy and data work; as a result, the time-to-decision for underwriting is significantly reduced. [12][13]. The mistakes commonly attributed to a lack of effort and manual data extraction are almost eliminated when data from various sources medical records, financial statements, and customer databases are automatically processed in parallel, yielding consistent, faster results.

Furthermore, the algorithms of artificial intelligence are very important in the pricing process because they can analyse vast volumes of historical data and identify complex risks that even the most sophisticated models have not yet detected. The system produces top-notch risk forecasting, which can then be used to set insurance rates that are fair to the insured and supportive of underwriting companies. [14].

Besides the fact that intelligent systems are increasing the productivity of the organisation by automating routine data processing and preliminary evaluations, raising human underwriters to concentrate on more complicated matters such as problem analysis, the development of new underwriting strategies, and customer relationship management [15]. The collaboration of AI agents and human skills makes the underwriting process more flexible, effective, and customer-oriented, benefiting both the insurer and the insured.

B. The Role of Human Expertise in Insurance Underwriting

Here are the key points of human experiences in insurance underwriting are as follow:

a) Contextual Awareness

A human underwriter is capable of understanding the nuances of a situation that are beyond the comprehension of AI. They can read between the lines and incorporate the larger context, which is crucial for underwriting decisions. [16]. The expectation is that, no matter how the cases are characterised, the human underwriters can see the wider picture and rely on the whole case and its context, rather than looking only at the information in isolation.

b) Policyholder Relationship Personalisation

Building and maintaining a good relationship with policyholders is a significant aspect of insurance underwriting. The human underwriters can present themselves at their best in direct communication, providing supportive advice and resolving individual problems for policyholders. [17]. In fact, this personal contact increases trust and loyalty, which are the main contributors to customer retention and satisfaction in the long run. Moreover, human underwriters can provide customers applying for underwritten products with the assurance they need, thereby making their experience more pleasant.

c) Judgment and Discretion

The underwriting process is positively affected by the professional judgment and discretion that an experienced human underwriter brings. Human underwriters can handle hard and ambiguous situations, make exceptions based on the singularity of each case, work through their prejudices and other factors to reach a decision that is practice-compliant, and take into account moral issues that are not part of algorithmic computation[18]. The participation of humans in the decision-making process is a key factor in underwriting that guarantees the fairness, legality, and alignment of decisions with the insurance company's goals and basic ethics.

C. Applications of AI in Financial Services

The applications of AI in the financial sector are such that human factors can be considered in AI decision-making systems (as shown in Figure 1):

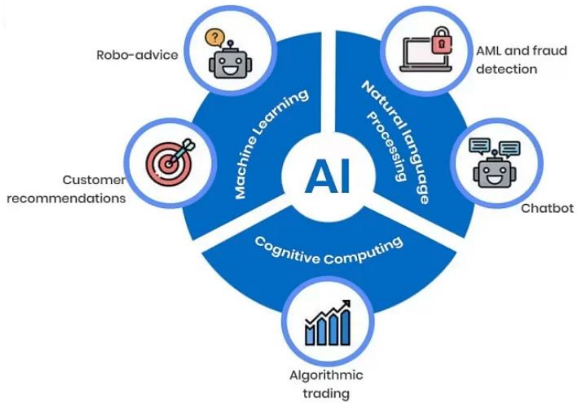

Figure 1: Application of AI in Financial Services

a) Robo-Advisory with Human Oversight:

Automated investment suggestions are the most notable attribute, but human decision-making is still part of the AI-backed robot-advisors' investment process, which ultimately guarantees the trust, transparency, and ethical decisions throughout the financial planning.

b) Personalized Customer Recommendations

The execution of the machine-learning (ML) models makes users' emotions and activities the main input for customized financial advice. [19] It is like mixing user's likes with the computer's, thus reducing the mind effort and increasing the choice satisfaction.

c) Fraud Detection and Ethical Decision-Making

AI technologies have a major impact on fraud detection and money laundering (AML) to detect patterns and monitor discrepancies [20][21], as well as managing human concerns like trust, accountability, and the comprehensibility of AI-related decisions.

d) AI-Driven Chatbots with Emotional Intelligence:

Cognitive computation makes use of natural language processing and sentiment analysis in unison, allowing chatbots to have a deeper understanding of user emotions and intents, thus, improving the quality of human–AI interaction.

e) Algorithmic Trading with Cognitive Load Optimization:

AI is significantly aiding the traders by performing the processing of huge volumes of financial data at a single go. This not only cuts down the mental exertion but also the accuracy of the decisions made through the application of AI insights plus systems that provide visual feedback is increased considerably [22][23]. All the above-mentioned applications denote that AI has not only been an instrument that polishes the financial industry’s efficiency and accuracy but also a partner that introduces human factors such as trust, cognitive load management, and interpretability to responsible, balanced decision-making.

D. Traditional Underwriting Challenges and Limitations

The Traditional underwriting procedures in P&C insurance mainly depend on predictive models, the collection of data by hand, and professional decision-making to arrive at the final conclusion. The aforementioned old-fashioned techniques are significantly slow, non-scalable, and non-adaptive to risk behaviour. An underwriting agent needs to review numerous documents such as property surveys, loss histories, and application forms for each case and also consider external risk factors, such as geographical hazards and economic conditions. Slow process brings about delays, which in turn affects both policy issuance and customer satisfaction [24][25]. What is more, traditional risk assessment methods are still not able to capitalize fully on unstructured data sources, which in turn affects the comprehensiveness of the assessment and may lead to the adopting of wrong pricing policies. Table I shows the underwriting technologies on human factors are given below:

Table 1: Evolution of Underwriting Technologies

Era	Technology Base	Data Sources	Processing Time	Decision Approach
Traditional (Pre-2000)	Manual processes, Basic actuarial models	Paper application, Limited databases	Days to weeks	Human judgment, Rule-based
Digital Transition (2000–2015)	Automated workflows, Statistical models	Digital forms, Internal databases	Hours to days	Hybrid human–computer
AI-Powered (2015–Present)	Machine learning, NLP, Predictive analytics	Multi-source integration, Real-time feeds	Minutes to hours	AI-assisted decision support
Next Generation (2025+)	Generative AI, Voice interfaces, Explainable AI (XAI)	IoT, Telematic, Ecosystem data	Real-time	Autonomous with human oversight

III. COGNITIVE LOAD IN AI-ASSISTED DECISION-MAKING.

AI-driven decision-making systems, especially in areas like underwriting and financial services, should factor in human cognitive limitations so that humans and machines can work together efficiently. One such relevant theory is Cognitive Load Theory (CLT), which offers useful insights into the design of AI interfaces that are mentally less taxing and help users better understand. [26]. When cognitive load is managed effectively, it results in higher decision accuracy and increases levels of trust, engagement, and a sense of control or confidence when using AI-enabled systems.

A. Understanding Cognitive Load Theory in AI Interactions

Cognitive Load Theory (CLT) is a theory formulated in the 1980s that examines a person's working memory capacity for handling information during learning and problem-solving tasks. According to the theory, cognitive load is divided into three types: intrinsic, extraneous, and germane. [27]. The intrinsic load is the difficulty of the material or the process to be learned, and the extraneous load, on the other hand, is the burden imposed by the way the information is presented, e.g., a badly designed interface or confusing instructions. The mental capacity to understand, structure, and relate new knowledge to old knowledge within the existing knowledge framework is what germane load consists of. CLT states that user-friendly systems, tools, and instructions are a prerequisite for overcoming human cognitive limits. This is when the discussion centres on AI interactions that do not overwhelm users with excessive information or unnecessary complexity. [28]. Proper AI design can reduce extraneous cognitive load. While there are disagreements regarding the general scope and the various interpretations of CLT, the underlying ideas still find their place in the context of human–AI interaction by providing, after all, clarity, usability, and cognitive efficiency.

B. Need for Cognition in Human-AI Decisions

The Need for Cognition (NFC) indicates how much a person enjoys and takes pleasure in cognitive tasks. It is common for people with high NFC to be more curious, to pay attention, and to learn hard things very easily, particularly when it comes to challenging cognitive tasks. [29][30]. Different NFC levels lead to different responses to AI-assisted decisions. The low-NFC user benefits from the AI's simple, clear explanations, which can also increase their trust in the system's recommendations. On the other hand, the high-NFC user feels restrained at times if the explanations limit the engagement of their analytical thinking. In areas like nutrition and decision-making, the high-NFC person is usually superior and finds the AI-supported task less mentally demanding, whereas the low-NFC person may view the system as more complex and thus require their full attention.

Researchers have discovered that applying cognitive forcing functions, which discourage non-analytical thinking, can further increase the NFC-user gap. To meet users' diverse cognitive needs, AI systems should be equipped with adaptive explanations, on-demand interpretability, and two-stage decision-making processes in which users first develop independent judgments and then integrate AI recommendations.

C. Reducing Cognitive Load for Underwriters

The predominant reason for the success of an AI assistant underwriting program is its ability to reduce cognitive burden. Intuitive AI interfaces that manage data hierarchically are one way to achieve this goal, as a result, the most important insights are displayed, while less important data is excluded. Through simplified dashboards, progressive disclosure and context-aware prompts, the user can do without non-trivial mental effort. Besides, visual and interactive explanations have great potential to reduce mental burden. The research on explainable AI (XAI) is well aware of the significance of visualization methods such as feature contribution graphs, decision trees, and counterfactual examples that help make AI outputs more understandable and, therefore, easier for human users to understand [31]. Interactive tools that allow browsing or configuring the inputs seem exciting since this reduces exposure to cognitive items.

Also, the use of adaptable automation and workflow matching makes AI support very similar to the user's skill level and the task's difficulty. The AI process that conforms to the present decision-making steps enables the brain to operate quicker, lessens cognitive load, and facilitates trust recalibration.

D. AI-Powered Underwriting Decision Support Systems

The AI underwriting agents' decision-support system role is probably the least questionable support for the humans during the decision-making process. Insurance companies are supposed to work with such systems and not against them. Hence, the premium pricing software determines the insurance policy rates by analyzing risk levels and the customer data according to the admissions criteria set by the company eventually leading to the identification of the customer’s ideal coverage and policy terms very quickly and automatically [32]. These systems not only generate risk assessments via their analyses but also take into consideration the company’s objectives thus securing it against losses and `gaining` a good reputation at the same time. Besides the use of complex mathematics in pricing models has made it possible for insurers to set up premiums that are not only based on risk but are also very competitive in the market.

The models that belong to this category are capable of coming up with optimal pricing strategies depending on the most precise elasticity estimates, competitive intelligence, and profitability objectives. The different situations can be evaluated to show how pricing decisions affect conversion rates, profits, and market share. Fraud detection systems are gaining importance in the underwriting decision-support process, thus, they are integrated throughout the entire process. The detectors apply e-commerce fraud detection techniques that have already been successful in the area to find suspicious activity in applications and mark cases with possible misrepresentation or fraudulent intent. ML algorithms use things like application inconsistencies, strange data patterns, and signs of past fraud to help find high-risk cases that need more investigation. The fraud detection procedure is not confined to the first underwriting; it also examines changes in policies and claims that may point to fraud.

IV. TRUST AND DECISION QUALITY IN HUMAN-AI COLLABORATION UNDERWRITING

AI-powered underwriting in a human-AI interaction setting is aided greatly by the trust and quality of decisions that are made, which are the main factors that ensure the correct operation of the system. The establishment of trust is a prerequisite if the underwriters intend to take advantage of the insights provided by AI while at the same time keeping their accountability and moral standards. A very effective partnership led to the rise of the accuracy, transparency, and fairness of the decisions made, because the human's judgment and context-derived insight empowered the AI's analysis and the decision, in turn, was confirmed by a human on the other side. Thus, finding this middle ground promotes trust, justice and reliability in situations where financial decision-making is extremely stressful and high stakes, such as in the case of insurance underwriting, for example.

A. Human–Gen AI Collaboration in Financial Services.

Generative AI (Gen AI) can produce text, images, videos, and even computer code that fit the context. It is the other way round with traditional AI systems that rely mainly on rule-based logical reasoning or predictive algorithms. Gen AI employs the latest deep learning (DL) architectures, such as transformer-based language models. In the financial services sector, Gen AI has taken over market analysis, investment planning, credit assessment, and report generation, among others, and has provided insights that surpass the structured results of traditional AI. [33]. These models are continually improved through reinforcement learning and human feedback, ensuring their outputs align with the institution's goals and priorities. AI-powered assistants, for example, are a strong testament to human-AI cooperation, where the AI handles incoming customer queries, generates reports, and allows human personnel to focus on strategic decision-making. [34].

Figure 2 shows the AI-powered underwriting process, which starts with customer onboarding and data profiling and ends with AI-powered risk assessment and dynamic pricing. The procedure proceeds to policy issuance, tailored product recommendations, and customer feedback collection, all of which drive continuous model learning and optimization to improve underwriting precision and operational efficiency.

Figure 2: Intelligent Policy Lifecycle with AI

According to the service quality principles, AI and humans working together in the financial sector are effective only if they are reliable, responsive, and assure customers of their privacy and security [35]. Rapid market changes and difficult data analyses require trustworthy and flexible systems as well as employees who are capable of turning real-time insights into faster and more accurate decision-making. Gen AI systems are, on the one hand, very powerful analytically and continuously responsive in customer service; on the other hand, human professionals offer critical judgment, ethical reasoning, and empathy, which are characteristics that no machines can imitate. The advent of Gen AI has, however, raised ethical issues besides hallucinations, biases, and opacity, which can not only dissolve trust but also make compliance in heavily regulated industries more difficult. Ultimately, the ongoing partnership between humans and AI, in which the experts of the field affirm, explain, and enhance the AI's insights, is what secures the dual outcomes of operational perfection and ethically sound AI usage in the financial decision-making process.

B. Trust in Human–AI Synergy in Decision-Making

One of the most crucial elements that affects how well humans and AI collaborate is trust. However, whereas interpersonal trust is a form of trust between two humans, trust in AI is a fundamentally different concept because AI lacks consciousness and is not guided by human-like intentions. To this end, several studies in this field have been conducted, in which users were surveyed on AI's reliability, transparency, and competence in healthcare, service marketing, and organizational decision-making.

Among the factors that lead to trust are transparency, feedback, fairness, and interpretability, which, in turn, affect users' trust in AI. Trust in AI in the healthcare sector means that AI recommendations and decision support are welcomed by patients and practitioners. [36]. The level of trust in AI tools in the enterprise and service sectors thus determines how widely they are used and integrated into workflows. Moreover, trust in AI can change over time rather than remaining constant. Users' interactions, experiences, and outcomes with AI systems are what continuously build their trust or distrust in such systems. Long-term studies, at least, reveal that trust usually results from the continued interaction with AI systems demonstrating transparency, accuracy, and fairness, and thus, after an initial period of doubt due to errors or biased outcomes.

C. Human–AI Synergy in Decision Making

The human–AI synergy can generally be divided into three main streams:

- The first stream focuses on the roles of humans and AI, as well as the division of tasks during collaboration. AI can assume different roles such as facilitator, reviewer, expert advisor, or guide in human-machine collaborative decision-making. The evolution of AI automation has shifted the role of AI from a simple supporting tool to an active decision-maker, in turn leading to different forms of collaboration between humans and AI.
- The second stream is mainly focused on the transformation of the experience and perception of the user that AI systems have. The modification of users' attitudes, feelings, and satisfaction in various contexts, such as customer service, education, and healthcare, has been one of the areas affected by AI and is therefore the focus of this research [37]. Cognitive processing, trust sometimes directed at the AI and sometimes at its decisions—and the often-variable acceptance and understanding of the AI are influenced by both the AI's design and the user's personality.
- The third-stream gives top priority to the design, setup, and management of AI systems to improve their quality and trustworthiness significantly, thereby promoting the most effective human–AI interaction. This discipline proposes to alter system design for the better by beautifying AI, choosing presentational modes and technologies, and making both physical and mental interfaces for collaboration more user-friendly.

D. Challenges and Considerations

The advantages of AI-driven automated underwriting are substantial, yet its successful implementation and widespread adoption require overcoming several challenges. [38]. The implementation of AI-driven underwriting systems in Table II shows the main challenges faced. Among the issues are data privacy and security, integration with legacy systems, regulatory compliance, and the high cost of system modernization.

A. Data Privacy

The process of AI underwriting is based on a large amount of personal and sensitive information; thus, the privacy of that data has to be given the highest priority. Insurance companies have to comply with data protection regulations like GDPR and CCPA to avoid violations and possibly even hefty penalties.

B. Ethical Concerns

Artificial intelligence systems may inadvertently be biased via data and give out unjust and discriminatory underwriting. Transparency, fairness and accountability in its algorithm should be guaranteed to maintain trust in finance decisions of high stakes in public view.

C. Regulatory Compliance

AI-specific regulations are in constant flux; thus, insurers who guarantee transparency and provide reasons for automated decisions are under a lot of pressure. The "black box" nature of AI models is a major regulatory hurdle and a stumbling block to achieving compliance through governance.

D. Legacy System Integration

Outdated IT infrastructure is the main cause of limited AI utilization. The integration of new AI capabilities with existing systems is an expensive process that involves substantial changes in technology and the organization of an IT department; hence, insurers are investing millions in digital transformation projects.

Table 2: Barriers to AI Adoption in Insurance: A Quantitative Overview

Key Challenges in Implementing AI-Driven Underwriting	Percentage (%)
Data Privacy and Security	86
Legacy System Integration	71
Regulatory Compliance	67
Skill Gap	54
AI Decision-Making Maturity	58
AI Bias	12
Cost of System Modernisation	80
Explainability of AI Decisions	65

V. LITERATURE REVIEW

The studies reviewed have highlighted significant improvements in AI-supported underwriting, prioritizing automated risk assessment, smart decision-making, and adaptive learning to enhance the accuracy, transparency, and efficiency of the process, while also identifying issues of trust and cognitive alignment between humans and AI.

Vuković, Dekpo-Adza, and Matović (2025). Analysis has revealed some of the most significant trends, such as the growing adoption of blockchain, ML, and natural language processing technologies that are, to a great extent, reshaping financial operations and decision-making. The research additionally highlights the necessity of explainable AI (XAI) and strong governance structures to mitigate the perils of AI-enabled systems and to facilitate, inter alia, the characteristics of being transparent, fair, and accountable. In addition, it discusses the principal ethical and legal concerns. The non-existence of common frameworks for AI use in banking and finance is the most pronounced barrier among others that still lag behind despite big leaps forward. The conclusion encourages that the issue of the moral, legal and social perceptions fitting the technological frontier be approached by the use of creative review [39].

Sachan et al. (2024) highlights that before spending millions on AI initiatives, it is essential to verify the consistency of choices made by human underwriters and keep an eye on the data's capacity to capture a company's lending rules in order to provide a solid basis for a legitimate system. By concurrently evaluating several independent and contradictory pieces of information, the Evidential Reasoning-explainer approach estimates the probability mass as the degree of support for a particular loan application choice. By contrasting the subjective assessments of underwriters during manual financial underwriting with results predicted from data, it measures the variability in previous determinations. By bridging the gap between inconsistent prior judgments and the intended final, genuine decisions, consistency analysis enhances decision quality. [40].

Table III summarizes key studies on AI-powered underwriting, highlighting progress in automation and decision support, while noting gaps in trust, cognitive load, and ethical transparency within human–AI collaboration

Table 3: Summary of the Study on Human Factors in Ai-Powered Underwriting Systems

Authors (Year)	Study Focus	Methodology / Approach	Tools / Data Sources	Strengths	Limitations
Vuković, et.al. (2025)	Adoption of AI, ML, NLP, and blockchain in financial operations; ethical and regulatory implications	Systematic emerging technologies in finance	Literature-based analysis across AI, ML, NLP, and blockchain studies	Highlights the importance of explainable AI (XAI) and governance frameworks for transparency and fairness	Lacks empirical data validation; no standardised framework proposed for AI adoption
Sachan, et. al. (2024)	Auditing consistency in human underwriting and integrating AI for decision reliability	Evidential Reasoning-Explainer methodology to assess decision probability and variability	Historical underwriting data; comparison of human vs. data-driven outcomes	Introduces a novel explainability framework improving decision consistency and reliability	Focuses narrowly on loan underwriting; limited generalizability across broader financial sectors
Rahul et.al. (2023)	Trends and impacts of AI (ML, NLP, CV) in underwriting and insurance operations	Mixed-method review with quantitative and qualitative assessment	Case studies from insurance companies implementing AI solutions	Demonstrates operational efficiency, improved accuracy, and customer satisfaction	Lacks quantitative benchmarks; addresses ethical issues broadly without framework integration
Pareek et.al. (2023)	Bias detection and fairness in AI-driven underwriting models	Development of a fairness-centric, explainable AI framework	Application of XAI, fairness metrics, data sanitisation, and real-time monitoring techniques	Comprehensive strategy covering the entire AI lifecycle (pre- to post-deployment)	Theoretical and conceptual; lacks real-world empirical testing or deployment data
Owens et al. (2022)	Explainable AI (XAI) applications in the insurance value chain	Systematic literature review (419 articles from Scopus, IEEE, ACM, WoS)	Multidatabase screening and classification of XAI in insurance (claims, underwriting, pricing)	Extensive mapping of XAI methods across insurance functions; identifies dominant techniques (e.g., rule extraction)	Limited focus on user interaction or cognitive load aspects; primarily technical scope
Tekale et.al. (2022)	AI and predictive analytics in insurance underwriting and risk modelling	Review of machine learning models used in predictive underwriting	Models: GLMs, GBTs, Random Forests, DNNs; Data: policy/claims, geospatial, IoT, NLP	Comprehensive overview of advanced ML tools and hybrid modelling for loss prediction	Focuses on technical performance; lacks discussion of human-AI interpretability or ethical governance

Rahul (2023)explores the trends that have led to these revolutions and gives a wholesome view of the AI proceedings, technologies that automate the underwriting procedures, include computer vision, natural language processing, and ML. Additionally, it also features case studies of insurance companies which have already introduced AI and showed how the technology succeeded in making results more accurate, operations highly efficient, and customer satisfaction high. In the paper, the researcher quantitatively and qualitatively assesses AI performance throughout the underwriting process and concludes with recommendations to guide insurers as they implement AI. [41].

Pareek (2023) underwrites the position that AI models must be subjected to strict and comprehensive bias testing and argues for a layered methodology that embeds fairness indicators, data cleaning and transparency-improving capabilities. Using proficient and clear AI (XAI) methods and fairness-focused model structures, propose an extensive bias detection and reduction plan that covers the entire AI life cycle, from pre-processing to post-deployment monitoring. By integrating constant calibration loops and real-time fairness checks, this paper argues that insurance companies can not only reduce the risk of algorithmic unfairness but also promote a fair, law-abiding, and open future for underwriting systems. [42].

Owens et al. (2022) assesses the degree of explain ability of artificial intelligence (Al) applications in insurance business practice and research. Search phrases typical of (X)AI applications in insurance were used to filter 419 original research papers from the Web of Science, IEEE Xplore, ACM Digital Library, Scopus, and Business Source. The present state of the art in XAI is thoroughly examined and categorised in the insurance literature, demonstrating how common XAI techniques are across the insurance value chain. According to the report, XAI techniques are especially used in actuarial pricing, underwriting, and claims management. In the insurance value chain, simplification techniques such as knowledge distillation and rule extraction are recognised as the main XAI methodologies. [43].

Tekale and Rahu (2022) provide a review of the material developments in the insurance underwriting process in 2022, with references to AI and predictive analytics, as well as the application of ML techniques to predict loss and to customer segmentation. In addition to generalized linear models, carriers frequently use gradient-boosted trees, random forests, and deep neural networks in frequency-severity or Tweedie models. Such models were based on more robust data pipelines that comprised structured policy/claims histories, geospatial peril layers, and telematics/IoT streams with unstructured evidence, all processed with NLP and computer vision. Calibration and quantification of uncertainty increased the adequacy of the rate, referral thresholds, and survival models, and large-loss gates increased tail estimation. [44].

VI. CONCLUSION AND FUTURE WORK

AI-powered underwriting systems have significantly transformed insurance and financial services by automating routine tasks, enhancing accuracy, and enabling data-driven decision-making. Humans are still very much needed, no matter what machines can do in terms of situational awareness, decision-making based on moral standards, and providing one-on-one customer interactions. The combination of human and AI work depends on user-friendly interfaces, understandable outputs, and flexible workflows that reduce mental effort and improve decision quality. Cognitive Load Theory and the Need for Cognition emphasize the need to consider different user skills, thereby making AI tools available and trustworthy for all users. The areas of application seen as most important in the very near future are robot-advisory, fraud detection, algorithmic trading, and personalized recommendations, which highlight the advantages of incorporating human factors into AI decision systems. On the other hand, problems like data privacy, compliance with regulations, integration of legacy systems, ethical issues, and possible AI bias still block the way to complete acceptance of AI in various sectors. The solutions to these problems must be found to ensure that the relationship between AI and humans in underwriting is high in terms of trust, fairness, and quality, and that the AI remains a human-centred, reliable, and powerful player, even in the most critical financial decision-making areas.

Future research needs to primarily concentrate on the areas of explain ability enhancement, personalized AI interfaces according to cognitive profiles, algorithmic bias reduction, and AI integration with existing systems, thereby ensuring ethical, transparent, and efficient human–AI collaboration in underwriting and financial decision-making. Also, the application of real-time feedback systems and user-oriented training programs can go a long way to elevate trust and decision quality in the AI-assisted workflows.

VII. REFERENCES

[1] N. Malali, “The Role Of Devsecops In Financial Ai Models: Integrating Security At Every Stage Of Ai/Ml Model Development In Banking And Insurance,” IJETRM, vol. 6, no. 11, p. 218, 2022, doi: 10.5281/zenodo.15239176.

[2] V. Thaker, S. Rawal, H. Shukla, I. Dave, A. Jani, and M. Thaker, “The Dual Impact of Artificial Intelligence on Human Cognition: A Comprehensive Review,” J. Int. Commer. Law Technol., vol. 6, no. 1, pp. 34–35, Aug. 2025, doi: 10.61336/Jiclt/25-01-04.

[3] B. R. Ande, “Federated Learning and Explainable AI for Decentralized Fraud Detection in Financial Systems,” J. Inf. Syst. Eng. Manag., vol. 10, no. 35, pp. 48–56, 2025.

[4] J. Han and D. Ko, “Trust Formation, Error Impact, and Repair in Human–AI Financial Advisory: A Dynamic Behavioral Analysis,” Behav. Sci. (Basel)., vol. 15, no. 10, p. 1370, Oct. 2025, doi: 10.3390/bs15101370.

[5] Kishore Subramanya Hebbar, “AI-DRIVEN REAL-TIME FRAUD DETECTION USING KAFKA STREAMS IN FINTECH,” Int. J. Appl. Math., vol. 38, no. 6s, pp. 770–782, Oct. 2025, doi: 10.12732/ijam.v38i6s.433.

[6] L. Aquilino, C. Di Dio, F. Manzi, D. Massaro, P. Bisconti, and A. Marchetti, “Decoding Trust in Artificial Intelligence: A Systematic Review of Quantitative Measures and Related Variables,” Informatics, vol. 12, no. 3, p. 70, Jul. 2025, doi: 10.3390/informatics12030070.

[7] S. Dodda, N. Kamuni, J. S. Arlagadda, V. S. M. Vuppalapati, and P. Vemasan, "A Survey of Deep Learning Approaches for Natural Language Processing Tasks," Int. J. Recent Innov. Trends Comput. Commun., vol. 9, no. 12, Dec. 2021, doi: 10.1109/TNNLS.2020.2979670.

[8] W. Almutairi and I. Almatrodi, "Trust Under Bounded Rationality: Exploring Human-AI Interaction in Decision-Making Through Large Language Models," Sage Open, vol. 15, no. 4, Oct. 2025, doi: 10.1177/21582440251380135.

[9] R. Palwe, "Adaptive human: AI decision support for high-stakes financial advice," Int. J. Comput. Artif. Intell., vol. 6, no. 2, pp. 385–392, Jul. 2025, doi: 10.33545/27076571.2025.v6.i2e.226.

[10] S. Narne, S. Dodda, T. Adedoja, M. M. T. Ayyalasomayajula, and S. Chintala, "AI-Driven Decision Support Systems in Management: Enhancing Strategic Planning and Execution," Int. J. Recent Innov. Trends Comput. Commun., vol. 12, no. 1, pp. 268–276, 2024.

[11] C. Patel, "Integration of AI in Customer Relationship Management (CRM) for Improved Sales Outcomes," Int. J. Emerg. Res. Eng. Technol., vol. 6, no. 4, pp. 137–145, 2025, doi: 10.63282/3050-922X.IJERET-V6I4P117.

[12] S. R. P. Madugula and N. Malali, "AI-powered life insurance claims adjudication using LLMs and RAG Architectures," Int. J. Sci. Res. Arch., no. April, 2025, doi: 10.30574/ijsra.2025.15.1.0867.

[13] Y. Macha, "A Data-Driven Framework for Medical Insurance Cost Prediction Using Efficient AI Approaches," Int. J. Res. Anal. Rev., vol. 11, no. 4, pp. 887–893, 2024.

[14] S. K. Tiwari, "Quality Assurance Strategies in Developing High-Performance Financial Technology Solutions," Int. J. data Sci. Mach. Learn., vol. 05, no. 01, pp. 323–335, Jun. 2025, doi: 10.55640/ijdsml-05-01-26.

[15] S. Bhattacharya, G. Castignani, L. Masello, and B. Sheehan, "AI revolution in insurance: bridging research and reality," Front. Artif. Intell., vol. 8, Apr. 2025, doi: 10.3389/frai.2025.1568266.

[16] J. Tase, "Generative AI in Insurance Industries: Transforming Workflows and Enhancing Customer Experience," Int. Res. J. Eng. Technol., vol. 11, no. 07, pp. 511–524, 2024.

[17] B. R. Cherukuri, "AI-powered personalization: How machine learning is shaping the future of user experience," Int. J. Sci. Res. Arch., vol. 12, no. 1, pp. 3111–3126, Jun. 2024, doi: 10.30574/ijsra.2024.12.1.0961.

[18] R. J. S. K. Das and Y. Makin, "Behavioral Risk Tolerance in U.S. Retirement Planning Vs. Property Insurance: A Comparative Analysis," Int. J. Appl. Math., vol. 38, pp. 41–70, 2025.

[19] T. Kumar and V. Shah, "Leadership in digital transformation: Enhancing customer value through AI-driven innovation in financial services marketing," Int. J. Sci. Res. Arch., vol. 15, no. 3, pp. 618–627, Jun. 2025, doi: 10.30574/ijsra.2025.15.3.1767.

[20] V. Prajapati, "Exploring Machine Learning Models for Fraud Identification Through Credit Cards in Financial Market," in 2025 Global Conference in Emerging Technology (GINOTECH), 2025, pp. 1–6. doi: 10.1109/GINOTECH63460.2025.11076669.

[21] S. B. Karri, S. Gawali, S. Rayankula, and P. Vankadara, "AI Chatbots in Banking: Transforming Customer Service and Operational Efficiency," in Advancements in Smart Innovations, Intelligent Systems, and Technologies, 2025, pp. 61–81. doi: 10.3233/FAIA251498.

[22] D. R. Jaiswal, "Impact of AI in the General Insurance underwriting factors," Cent. Eur. Manag. J., vol. 31, pp. 697–705, 2023, doi: 10.57030/23364890.cemj.31.2.72.

[23] A. Parupalli, "The Evolution of Financial Decision Support Systems : The Evolution of Financial Decision Support Systems : From BI Dashboards to Predictive Analytics," KOS J. Bus. Manag., vol. 1, no. 1, pp. 1–8, 2025.

[24] H. V. R. Yeddula, "The Transformative Impact Of Ai On Insurance Underwriting: A Technical Analysis," Int. J. Res. Comput. Appl. Inf. Technol., vol. 8, no. 1, pp. 2214–2229, Feb. 2025, doi: 10.34218/IJRCAIT_08_01_161.

[25] A. R. Bilipelli, "Forecasting the Evolution of Cyber Attacks in FinTech Using Transformer-Based Time Series Models," Int. J. Res. Anal. Rev. | Ijrar.Org, vol. 10, no. 3, pp. 383–389, 2023, [Online]. Available: https://www.ijrar.org/papers/IJRAR23C3692.pdf

[26] Srinivasa Rao Kurakula, "The Role of AI in Transforming Enterprise Systems Architecture for Financial Services Modernization," J. Comput. Sci. Technol. Stud., vol. 7, no. 4, pp. 181–186, 2025, doi: 10.32996/jcsts.2025.7.4.21.

[27] M. Fox, G. Vaidyanathan, and J. L. Breese, "The Impact Of Artificial Intelligence On Musicians," Issues Inf. Syst., vol. 25, no. 3, pp. 267–276, 2024, doi: 10.48009/3_iis_2024_121.

[28] N. Malali, "Exploring Artificial Intelligence Models for Early Warning Systems with Systemic Risk Analysis in Finance," in 2025 International Conference on Advanced Computing Technologies (ICoACT), 2025, pp. 1–6. doi: 10.1109/ICoACT63339.2025.11005357.

[29] F. M. Cau and L. D. Spano, "Exploring the Impact of Explainable AI and Cognitive Capabilities on Users' Decisions," pp. 1–44, May 2025.

[30] Tanmaykumar Vithaldas Shah, "Leadership in digital transformation: Enhancing customer value through AI-driven innovation in financial services marketing," Int. J. Sci. Res. Arch., vol. 15, no. 3, pp. 618–627, Jun. 2025, doi: 10.30574/ijsra.2025.15.3.1767.

[31] H. Tejeda, A. Kumar, P. Smyth, and M. Steyvers, "AI-Assisted Decision-making: a Cognitive Modeling Approach to Infer Latent Reliance Strategies," Comput. Brain Behav., vol. 5, no. 4, pp. 491–508, Dec. 2022, doi: 10.1007/s42113-022-00157-y.

[32] A. Parupalli, "The Evolution of Financial Decision Support Systems : From BI Dashboards to Predictive Analytics," KOS J. Bus. Manag., vol. 1, no. 1, pp. 1–8, 2023.

[33] Ruhul Quddus Majumder, "A Review of Anomaly Identification in Finance Frauds Using Machine Learning Systems," Int. J. Adv. Res. Sci. Commun. Technol., vol. 5, no. 10, pp. 101–110, Apr. 2025, doi: 10.48175/IJARSCT-25619.

[34] C. Xu and S.-E. Cho, "Factors Affecting Human–AI Collaboration Performances in Financial Sector: Sustainable Service Development Perspective," Sustainability, vol. 17, no. 10, p. 4335, May 2025, doi: 10.3390/su17104335.

[35] H. P. Kapadia and K. C. Chittoor, "AI Chatbots for Financial Customer Service: Challenges & Solutions," J. Adv. Futur. Res., vol. 2, no. 2, pp. 1–7, 2024.

[36] A. Pathak and V. Bansal, "AI as decision aid or delegated agent: The effects of trust dimensions on the adoption of AI digital agents," Comput. Hum. Behav. Artif. Humans, vol. 2, no. 2, p. 100094, Aug. 2024, doi: 10.1016/j.chbah.2024.100094.

[37] Y. Bao, W. Gong, and K. Yang, "A Literature Review of Human–AI Synergy in Decision Making: From the Perspective of Affordance Actualization Theory," Systems, vol. 11, no. 9, p. 442, Aug. 2023, doi: 10.3390/systems11090442.
[38] P. K. Peddamukkula, "The Impact of AI-Driven Automated Underwriting on the Life Insurance Industry," Int. J. Innov. Resarch Sci. Eng. Technol., vol. 7, no. 5, Jun. 2024, doi: 10.15680/1a1fxe57.
[39] D. B. Vuković, S. Dekpo-Adza, and S. Matović, "AI integration in financial services: a systematic review of trends and regulatory challenges," Humanit. Soc. Sci. Commun., vol. 12, no. 1, p. 562, Apr. 2025, doi: 10.1057/s41599-025-04850-8.
[40] S. Sachan, F. Almaghrabi, J.-B. Yang, and D.-L. Xu, "Human-AI collaboration to mitigate decision noise in financial underwriting: A study on FinTech innovation in a lending firm," Int. Rev. Financ. Anal., vol. 93, p. 103149, May 2024, doi: 10.1016/j.irfa.2024.103149.
[41] N. Rahul, "Transforming Underwriting with AI: Evolving Risk Assessment and Policy Pricing in P&C Insurance," Int. J. AI, BigData, Comput. Manag. Stud., vol. 4, no. 3, 2023, doi: 10.63282/3050-9416.IJAIBDCMS-V4I3P110.
[42] C. S. Pareek, "Unmasking Bias: A Framework for Testing and Mitigating AI Bias in Insurance Underwriting Models," J. Artif. Intell. Mach. Learn. Data Sci., vol. 1, no. 1, pp. 1736–1741, Nov. 2023, doi: 10.51219/JAIMLD/Chandra-shekhar-pareek/377.
[43] E. Owens, B. Sheehan, M. Mullins, M. Cunneen, J. Ressel, and G. Castignani, "Explainable Artificial Intelligence (XAI) in Insurance," Risks. 2022. doi: 10.3390/risks10120230.
[44] K. M. Tekale and N. Rahu, "AI and Predictive Analytics in Underwriting, 2022 Advancements in Machine Learning for Loss Prediction and Customer Segmentation," Int. J. Artif. Intell. Data Sci. Mach. Learn., vol. 3, no. 1, 2022, doi: 10.63282/3050-9262.IJAIDSML-V3I1P111.