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Redefining work and building organizational agility through artificial intelligence in selected financing and lending institutions

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Abstract

This study examines how artificial intelligence (AI) adoption reshapes work and enhances organizational agility in selected financing and lending institutions in Cabanatuan City, Philippines, guided by Sociotechnical Systems (STS) Theory. Using a quantitative descriptive–correlational design, data were collected from 120 managers and employees across 20 institutions through a validated survey instrument. The study assessed AI adoption across the social subsystem (redefinition of human roles, employee adaptation, and engagement), technical subsystem (AI capability, task–technology fit, and system usability), and the human–technology interface (human–AI collaboration quality and workflow integration). Descriptive and inferential analyses, including Pearson correlation and structural modeling, were employed. Results reveal strong and statistically significant relationships between the social and technical subsystems ($r = 0.909$, $p < 0.01$) and between the technical subsystem and the human–technology interface ($r = 0.922$, $p < 0.01$). Findings indicate that AI functions primarily as a complementary tool, enhancing employee adaptability, engagement, decision quality, and workflow efficiency rather than replacing human roles. The study contributes empirical evidence supporting the joint optimization of human and technological elements and offers policy directions for human-centered, ethical, and agile AI integration in financial institutions.

Keywords: *sociotechnical systems, employee adaptation, employee engagement, human–AI collaboration*

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1. Introduction

Artificial Intelligence (AI) rapidly transforming organizational landscapes by automating processes, enhancing decision-making, and reshaping traditional work structures. In the financial sector, particularly in financing and lending institutions, AI is increasingly utilized in areas such as credit assessment, customer service, fraud detection, and data management. While much of the discourse on AI emphasizes efficiency and productivity, its broader implications on human roles, workplace dynamics, and organizational adaptability remain underexplored. AI systems are highly effective in processing large volumes of data; however, they lack essential human capabilities such as creativity, empathy, and ethical judgment (Frey & Osborne, 2017; Tarafdar et al., 2019).

This limitation highlights the importance of positioning AI as a complementary tool rather than a replacement for human labor. Supporting this perspective, Jarrahi (2018) introduced the concept of human–AI symbiosis that optimal decision-making emerges from the integration of machine intelligence and human judgment, particularly in complex and uncertain environments. Despite increasing adoption, there remains limited research on how AI affects employee adaptation, engagement, and organizational flexibility. Most studies focus on technological advancements, with less attention given to the interaction between human and technical components in the workplace. Addressing this gap requires a holistic framework that considers both dimensions simultaneously, as successful AI implementation depends not only on technological capability but also on effective human-AI interaction.

This study is anchored in Sociotechnical Systems (STS) Theory, primarily attributed to Eric Trist and Fred Emery, which posits that organizational effectiveness is achieved through the joint optimization of social and technical subsystems. The social subsystem includes human roles, skills, and adaptability, while the technical subsystem encompasses AI capabilities, task–technology fit, and system usability. The alignment of these subsystems enables effective human–AI collaboration, seamless workflow integration, and improved organizational agility.

This study explores how adopting AI is changing work and helping financing and lending institutions in Cabanatuan City become more agile. Using STS Theory as a guide, the research looks at how social and technical subsystems work together to improve the way people and technology interact, leading to better long-term results for organizations. This study tests the following hypotheses:

HO1: There is no significant relationship between the social subsystem and the technical subsystem in the adoption of AI.

HO2: There is no significant relationship between the technical subsystem and the human–technology interface.

The study contributes to both theory and practice. Theoretically, it extends STS Theory by demonstrating the interdependence of human and technological elements in AI-driven environments. Practically, it provides evidence-based insights to guide leaders, policymakers, and technology developers in designing AI strategies that balance innovation with workforce development. Ultimately, the study promotes a human-centered approach to AI adoption that enhances employee engagement, supports organizational flexibility, and fosters sustainable, agile, and resilient workplaces in the evolving digital economy.

2. Literature Review

According to Lazo and Ebardo (2023), based on 35 reviewed studies on AI adoption in banking, existing research largely focuses on banks and customers, while the perspectives of regulators and service providers remain less examined. Most of the studies describe the industry experience on AI adoption and its implications to operations (i.e. Pesa et al., 2026; Samonte et al., 2024). Hence, there is a need for further empirical research on stakeholder cooperation, workforce capabilities, and responsible AI adoption. AI adoption should not be viewed solely as a technological issue but also as an organizational and human-centered process. On the other hand, empirical evidence shows that organizational, technological, skills, cost, and regulatory challenges that may hinder AI adoption (Sinha & Lee, 2024; Distor & Neumann, 2026; Lopez-Garcia & Rojas, 2024).

In the Philippine context, Pesa et al. (2026) examined digital financial platform engagement and AI deployment using national financial-access data and qualitative insights from financial institutions and policy experts and found that financial institutions are strategically deploying AI to improve access, security, and user experience. However, smaller cooperatives and savings and loan associations continue to face structural and resource-related barriers to AI adoption. The AI implementation in Philippine financial services varies according to institutional capacity and resources. Hence, there is a need to examine how organizations and employees adapt to AI-enabled work systems.

Although studies provide important evidence on AI adoption in financial services, limited empirical research has examined how AI reshapes employees' roles, adaptation, engagement, and interactions with technology within financing and lending institutions. This study addresses this gap by examining selected financing and lending institutions in Cabanatuan City through a Sociotechnical Systems perspective, focusing on the alignment of social and technical subsystems and the human-technology interface.

3. Methodology

This study utilized a quantitative-descriptive and correlational research design to examine how AI adoption influences the interaction between social and technical subsystems in financing and lending institutions. The research was conducted in 20 selected institutions in Cabanatuan City, Nueva Ecija, with a total of 120 participants composed of managers and employees who are directly involved in or exposed to AI-supported processes. A purposive–quota sampling technique was employed to ensure representation across organizational roles, capturing both managerial and operational perspectives consistent with STS framework.

Table 1

Profile of the financing and lending institutions

Variables	Frequency	Percentage
Years Operation		
1 to 5 years	5	25%
6 to 10 years	2	10%
11 to 20 years	3	15%
More than 20 years	10	50%
Forms of Business		
Corporation	14	70%
Cooperative	4	20%
Others	2	10%
Number of Employees		
1 to 49 employees	8	40%
50 to 249 employees	4	20%
More than 250 employees	8	40%
Products/Services (Multiple Response Item)		
Loan products	19	95%
Insurance products	3	15%
Deposits and savings	5	25%
Leasing services	2	10%
Others	1	5%
Annual Revenue		
Below P10 million	8	40%
10 million to less than P50 million	4	20%
P50 million to less than P200 million	2	10%
P200 million to P1 billion	2	10%
Above P1 billion	2	10%
Prefer not to say	2	10%

Table 1 presents the profile of the 20 financing and lending institutions that participated in the study in terms of years of operation, form of business, number of employees, products and services, and annual revenue. Half (50%) of the institutions had been operating for more than 20 years, while 25% had operated for 1–5 years and another 25% for 6–20 years. In terms of business form, 70% were corporations, 20% were cooperatives, and 10% represented other forms of business. Regarding workforce size, 40% employed 1–49 employees, 20% employed 50–249 employees, and 40% employed more than 250 employees. In terms of products and services, 95% offered loan products, 25% provided deposits and savings, 15% offered insurance, 10% provided leasing, and 5% offered other financial services. Annual revenue also varied considerably, with 40% reporting less than ₱10 million, 20% reporting ₱10 million to less than ₱50 million, 10% reporting ₱50 million to less than ₱200 million, 10% reporting ₱200 million to ₱1 billion, 10% reporting more than ₱1 billion, and 10% not disclosing their revenue.

Table 2

Profile of the participants

Variables	Frequency	Percentage
Age		
20-29 years old	58	48.3%
30-39 years old	41	34.2%
40-49 years old	21	17.5%
Sex		
Male	52	43.3%
Female	63	52.5%
Prefer not to say	5	4.2%
Highest Educational Attainment		
Undergraduate/Vocational	6	5%
College Graduate	110	91.67%
Master’s Degree Holder	4	3.33%
Number of Years		
1 to 3 years	60	50%
4 to 10 years	38	31.67%
11 to 20 years	21	17.50%
More than 20 years	1	0.83%
AI/System usage		
Yes	88	73.33%
No	32	26.67%
Adoption stage		
Not yet started	42	35%
Testing Phase	20	16.67%
Partially adopted	32	26.67%
Fully integrated	26	21.67%
Total	**120**	**100%**

As shown in Table 2, the participants were predominantly young, with 48.3% aged 20–29 years, 34.2% aged 30–39 years, and 17.5% aged 40–49 years; younger employees have generally demonstrated stronger behavioral intentions and actual use of emerging technologies (Fazi et al., 2024). In terms of sex, 52.5% were female, 43.3% were male, and 4.2% did not disclose their sex. Regarding educational attainment, 91.67% were college graduates, 5.00% had vocational or undergraduate backgrounds, and 3.33% held master's degrees. In terms of years of service, 50.00% had 1–3 years of service, 31.67% had 4–10 years, and 17.50% had 11–20 years. With respect to AI or system usage, 73.33% reported using AI or system-based tools in their daily work, while 26.67% reported no direct use, indicating substantial exposure to technology-enabled tools among the participants, consistent with the increasing adoption of AI across workplace sectors (Crane et al., 2025). Finally, 35.00% reported that AI implementation had not yet started, 16.67% indicated that AI was being tested, 26.67% reported partial adoption, and 21.67% reported full integration, showing that 51.67% were in the non-implementation or testing stages, whereas 48.34% were in the partial or full integration stages.

Data were collected using a structured survey questionnaire developed based on the study objectives and STS constructs, covering participant profile, social subsystem, technical subsystem, human–technology interface, and proposed policy outcomes. Responses were measured using a four-point Likert scale. The instrument underwent content validation by experts and pilot testing to ensure reliability, with Cronbach's alpha values meeting the acceptable threshold of 0.70. Construct validity was assessed through Exploratory Factor Analysis, and where applicable, Confirmatory Factor Analysis using SmartPLS.

Data collection was conducted through both online and printed questionnaires upon securing institutional permission, with participants informed of the study's purpose and assured of confidentiality. Ethical standards were strictly observed, ensuring voluntary participation, informed consent, anonymity, and secure handling of data. The collected data were analyzed using descriptive statistics such as frequency, percentage, weighted mean, and standard deviation, as well as inferential tools including Pearson correlation, multiple regression, and Structural Equation Modeling to examine relationships among variables. All analyses were performed at a 0.01 level of significance.

4. Findings and Discussions

This study examines how adopting AI is changing work and helping financing and lending institutions in Cabanatuan City become more agile. Using STS Theory as a guide, the research looks at how social and technical subsystems work together to improve the way people and technology interact, leading to better long-term results for organizations.

Table 3

Adoption of artificial intelligence (AI) in terms of the social subsystem redefinition of human roles

Indicators	Wm	Description
1. System/AI has changed the nature of my daily job responsibilities.	2.90	Agree
2. My current tasks now require more analytical or creative skills because of AI.	2.67	Agree
3. System/AI has automated some of my previous manual or repetitive duties.	2.80	Agree
4. My role now involves supervising or validating AI-generated outputs.	2.61	Agree
5. The introduction of System/AI has expanded my range of responsibilities.	2.75	Agree
6. I am expected to make higher-level decisions supported by AI tools.	2.82	Agree
7. My job has become more strategic since the adoption of System/AI.	2.86	Agree
8. System/AI has influenced how I define the purpose of my work.	2.73	Agree
Overall Weighted Mean	**2.77**	**Agree**

Legend: 3.25-4.00 Strongly Agree; 2.50-3.24 Agree; 1.75-2.49 Disagree; 1.00-1.74 Strongly Disagree

Table 3 presents the adoption of AI in terms of the social subsystem, specifically the redefinition of human roles. The results show an overall weighted mean of 2.77, interpreted as “Agree,” indicating that participants generally perceive AI as changing rather than replacing human roles. The highest-rated indicator was the change in daily job responsibilities (WM = 2.90), followed by the shift toward more strategic work (WM = 2.86). participants also agreed that AI has increased expectations for higher-level decision-making (WM = 2.82) and automated routine tasks (WM = 2.80). Meanwhile, the need for more analytical or creative skills (WM = 2.67) and supervision of AI outputs (WM = 2.61) received comparatively lower, but still affirmative, ratings.

The AI adoption is associated with changes in employees’ responsibilities, particularly through task automation and greater involvement in strategic and decision-making activities. The findings support existing literature that AI complements human capabilities by assisting decision-making and enabling employees to focus on higher-value analytical and strategic tasks (Jarrahi, 2018).

Table 4

Adoption of artificial intelligence (AI) in terms of the social subsystem employee adaptation

Indicators	Wm	Description
1. I easily adapt to new System/AI tools and systems used in my organization.	2.99	Agree
2. I feel confident when learning to use System/AI-related technologies.	2.99	Agree
3. I actively seek opportunities to improve my System/AI-related skills.	3.02	Agree
4. My organization provides sufficient training to help me adapt to AI changes.	2.79	Agree
5. I am open to changing the way I work when new AI systems are introduced.	2.99	Agree
6. I can handle challenges or errors that occur while using AI systems.	2.81	Agree
7. I consider AI adoption an opportunity for personal and career growth.	3.03	Agree
8. I adjust my workflow quickly when System/AI tools are integrated into our processes.	2.95	Agree
Overall Weighted Mean	**2.95**	**Agree**

Legend: 3.25-4.00 Strongly Agree; 2.50-3.24 Agree; 1.75-2.49 Disagree; 1.00-1.74 Strongly Disagree

Table 4 presents employee adaptation to System/AI integration. The results show an overall weighted mean of 2.95, interpreted as "Agree," that participants generally demonstrate adaptability to AI-enabled work environments. The highest-rated indicators were perception of AI as an opportunity for personal and career growth (WM = 3.03) and willingness to pursue skill development (WM = 3.02). Participants also agreed on their confidence in learning AI-related technologies (WM = 2.99) and openness to changing work practices (WM = 2.99). This was followed by their ability to quickly adjust workflows (WM = 2.95) and ability to handle system-related challenges (WM = 2.81). Organizational training and support received the lowest rating (WM = 2.79), although it remained within the "Agree" range.

Employee adaptability is driven by both individual initiative and organizational support mechanisms. This finding is consistent with Tarafdar et al. (2019) that employees engaged in skill development and receptive to technological change are more likely to adapt successfully to digital transformation, including AI adoption.

Table 5 presents the participants' assessment of AI adoption in terms of employee engagement. The results show an overall weighted mean of 2.83, interpreted as "Agree," indicating a generally positive assessment of AI's contribution to employee engagement. The highest-rated indicator was allocation of more time to meaningful tasks (WM = 2.93), followed by enhanced overall productivity (WM = 2.87) and increased enthusiasm for work (WM = 2.83). participants also agreed that AI contributes to motivation (WM = 2.79), involvement in AI-related decisions (WM = 2.79), teamwork and collaboration (WM = 2.81), and recognition for effective AI use (WM = 2.78). Although recognition for effective AI use received the lowest rating, it remained within the "Agree" range.

Table 5

Adoption of artificial intelligence (AI) in terms of the social subsystem employee engagement

Indicators	Wm	Description
1. System/AI allows me to spend more time on meaningful tasks.	2.93	Agree
2. I feel more productive when working with AI tools.	2.87	Agree
3. AI-based systems motivate me to perform better.	2.79	Agree
4. I feel involved in decisions regarding System/AI implementation in our workplace.	2.79	Agree
5. System/AI initiatives in our organization promote teamwork and collaboration.	2.81	Agree
6. The use of System/AI has increased my enthusiasm for work.	2.83	Agree
7. I feel recognized when I use System/AI effectively in my role.	2.78	Agree
8. Overall, System/AI contributes positively to my engagement and motivation.	2.88	Agree
Overall Weighted Mean	**2.83**	**Agree**

Legend: 3.25-4.00 Strongly Agree; 2.50-3.24 Agree; 1.75-2.49 Disagree; 1.00-1.74 Strongly Disagree

AI adoption supports employee engagement by streamlining work processes and enabling more value-driven activities, without diminishing employees' sense of involvement or motivation. Appropriately designed digital technologies can enhance engagement by enriching work roles, supporting autonomy, and reducing repetitive tasks (Parker & Grote, 2022).

Table 6

AI adoption responds to changes in terms of technical subsystem AI capability

Indicators	Wm	Description
1. AI systems in our organization effectively automate routine tasks.	2.85	Agree
2. AI tools help improve the accuracy of work processes.	2.97	Agree
3. AI systems provide data-driven insights for decision-making.	2.95	Agree
4. AI tools enhance the organization's productivity.	2.95	Agree
5. AI applications contribute to innovation in our workplace.	2.93	Agree
6. The AI systems are capable of analyzing complex data.	2.93	Agree
7. AI technologies help predict and solve business problems.	2.83	Agree
8. Overall, our organization's AI tools are reliable and effective.	2.93	Agree
Overall Weighted Mean	**2.92**	**Agree**

Legend: 3.25-4.00 Strongly Agree; 2.50-3.24 Agree; 1.75-2.49 Disagree; 1.00-1.74 Strongly Disagree

Table 6 presents AI adoption in terms of the technical subsystem, specifically AI capability. The results show an overall weighted mean of 2.92, interpreted as "Agree," indicating that participants generally perceive the AI capabilities of their institutions as adequate and functional. The highest-rated indicator was improvement in accuracy (WM = 2.97), followed by enhanced productivity (WM = 2.95) and support for data-driven decision-making (WM = 2.95). participants also agreed that AI can analyze complex data (WM = 2.93) and foster innovation (WM = 2.93). Meanwhile, automation of routine tasks received a WM of 2.85, which was the lowest among the indicators but remained within the "Agree" range.

AI capability contributes to technical subsystem performance through improved accuracy, productivity, data analysis, decision-making, automation, and innovation. The role of AI and advanced technologies is significant in automating routine tasks, generating data-driven insights, and enhancing organizational capabilities (Brynjolfsson & McAfee, 2017).

Table 7

AI adoption responds to changes in terms of technical subsystem task-technology fit

Indicators	Wm	Description
1. The System/AI tools match the tasks I perform in my job.	2.85	Agree
2. System/AI tools complement my skills and expertise.	2.78	Agree
3. The technology helps me complete my work more effectively.	2.98	Agree
4. There is a good match between my job requirements and AI functionalities.	2.86	Agree
5. System/AI reduces the time needed to complete my tasks.	2.97	Agree
6. System/AI tools improve the quality of my output.	2.93	Agree
7. I can easily integrate System/AI into my daily workflow.	2.90	Agree
8. Overall, the AI technology fits well with the nature of my job.	2.98	Agree
Overall Weighted Mean	**2.91**	**Agree**

Legend: 3.25-4.00 Strongly Agree; 2.50-3.24 Agree; 1.75-2.49 Disagree; 1.00-1.74 Strongly Disagree

Table 7 presents the participants' assessment of AI adoption in terms of task–technology fit. The results show an overall weighted mean of 2.91, interpreted as "Agree," indicating that participants generally perceive AI technologies as aligned with their job requirements. The highest-rated indicators were AI helps complete work more effectively (WM = 2.98) and reduces the time required to accomplish tasks (WM = 2.97). These were followed by improvement in output quality (WM = 2.93) and ease of workflow integration

(WM = 2.90). The lowest-rated indicator was AI complement users' skills (WM = 2.78), although it remained within the "Agree" range.

AI tools are generally compatible with job requirements and contribute to work efficiency, output quality, and workflow integration, congruent with the Task–Technology Fit theory of Goodhue and Thompson (1995). Technology contributes to individual performance when its functionalities are aligned with task requirements. The results demonstrate this alignment through the positive ratings for work effectiveness, task completion time, output quality, and workflow integration.

Table 8

AI adoption responds to changes in terms of technical subsystem system usability

Indicators	Wm	Description
1. The AI systems are easy to use and understand.	2.98	Agree
2. I can operate System/AI tools with minimal technical support.	2.94	Agree
3. AI systems provide data-driven insights for decision-making.	2.88	Agree
4. System/AI tools enhance the organization's productivity.	2.96	Agree
5. System/AI applications contribute to innovation in our workplace.	2.94	Agree
6. The AI systems are capable of analyzing complex data.	2.93	Agree
7. System/AI technologies help predict and solve business problems.	2.83	Agree
8. Overall, our organization's System/AI tools are reliable and effective.	2.93	Agree
Overall Weighted Mean	**2.92**	**Agree**

Legend: 3.25-4.00 Strongly Agree; 2.50-3.24 Agree; 1.75-2.49 Disagree; 1.00-1.74 Strongly Disagree

Table 8 presents system usability within the technical subsystem. The results show an overall weighted mean of 2.92, interpreted as "Agree," indicating that participants generally perceive AI systems as usable and accessible. The highest-rated indicator was AI tools are easy to understand and use (WM = 2.98), followed by productivity enhancement (WM = 2.96) and operation with minimal technical support (WM = 2.94). Participants also agreed that AI contributes to innovation (WM = 2.94), analyzes complex data (WM = 2.93), and provides decision-making insights (WM = 2.88).

AI systems are perceived as relatively easy to use while supporting productivity, innovation, data analysis, and decision-making. Similarly, Davis's (1989) Technology Acceptance Model (TAM) identifies perceived ease of use as an important factor influencing technology acceptance and use. The positive usability ratings suggest that the accessibility and ease of operation of AI systems may support their continued use in organizational work processes.

Table 9

Influence of changes in the human–technology interface to the alignment between the social and technical subsystems in terms of human-AI collaboration quality

Indicators	Wm	Description
1. System/AI improves the quality of my decision-making.	2.84	Agree
2. I can effectively combine my expertise with AI-generated insights.	2.86	Agree
3. System/AI helps me accomplish tasks more efficiently.	2.92	Agree
4. System/AI complements my work rather than replacing it.	2.91	Agree
5. Collaboration between humans and System/AI improves team performance.	2.93	Agree
6. I feel confident working alongside System/AI tools.	2.89	Agree
7. System/AI provides meaningful support in complex problem-solving.	2.83	Agree
8. The interaction between humans and System/AI enhances overall productivity.	2.98	Agree
Overall Weighted Mean	**2.89**	**Agree**

Legend: 3.25-4.00 Strongly Agree; 2.50-3.24 Agree; 1.75-2.49 Disagree; 1.00-1.74 Strongly Disagree

Table 9 presents the influence of changes in the human–technology interface in terms of human–AI collaboration quality. The results show an overall weighted mean of 2.89, interpreted as “Agree,” indicating a generally positive assessment of collaboration between employees and AI systems. The highest-rated indicator was AI enhances productivity (WM = 2.98), followed by AI improves team performance (WM = 2.93) and AI increases task efficiency (WM = 2.92). participants also agreed that AI complements rather than replaces human effort (WM = 2.91), supports decision-making (WM = 2.84), and assists in complex problem-solving (WM = 2.83).

AI is perceived as a complementary technology that supports productivity, teamwork, task efficiency, decision-making, and problem-solving. In addition, AI generates greater organizational value when it augments rather than replaces human capabilities (Davenport & Ronanki, 2018). The positive ratings suggest that human–AI collaboration can support the alignment of human expertise and technological capabilities within the workplace.

Table 10 presents the influence of changes in the human–technology interface in terms of workflow integration. The results show an overall weighted mean of 2.89, interpreted as “Agree,” indicating a generally positive assessment of AI integration into organizational workflows. The highest-rated indicator was improvement in overall workflow efficiency (WM = 2.99), followed by streamlining of processes (WM = 2.94) and minimization of task delays (WM = 2.93). Participants also agreed that AI enhances coordination across teams (WM = 2.87) and supports smooth transitions between human and system tasks (WM = 2.87). In addition, AI was perceived as a natural component of daily operations (WM = 2.83), while tasks are effectively distributed between employees and intelligent systems (WM = 2.86).

Table 10

Influence of changes in the human–technology interface to the alignment between the social and technical subsystems in terms of workflow integration

Indicators	Wm	Description
1. AI systems are seamlessly integrated into our work processes.	2.85	Agree
2. System/AI improves the coordination between departments and teams.	2.87	Agree
3. System/AI has streamlined our workflow and reduced unnecessary steps.	2.94	Agree
4. Work transitions between humans and System/AI occur smoothly.	2.87	Agree
5. System/AI integration minimizes delays in completing tasks.	2.93	Agree
6. Tasks are efficiently distributed between employees and AI tools.	2.86	Agree
7. System/AI is now a natural part of our organization's daily operations.	2.83	Agree
8. Overall, System/AI integration has improved workflow efficiency.	2.99	Agree
Overall Weighted Mean	**2.89**	**Agree**

Legend: 3.25-4.00 Strongly Agree; 2.50-3.24 Agree; 1.75-2.49 Disagree; 1.00-1.74 Strongly Disagree

AI is perceived to support workflow efficiency, process streamlining, coordination, task continuity, and work distribution. The results suggest that AI integration facilitates the interaction between employees and technical systems within organizational workflows. This is consistent with Lacity and Willcocks (2017), who emphasized that intelligent automation can improve process efficiency and coordination when integrated with existing organizational roles and routines.

Table 11 presents the relationship between the social and technical subsystems in AI adoption. The results show a very strong positive correlation between the two subsystems ($r = 0.909$, $p < .001$), indicating a statistically significant relationship at the 0.01 level. This means that higher assessments of social subsystem factors, including employee adaptation, engagement, and redefinition of human roles, are associated with higher assessments of technical subsystem factors, including AI capability, task–technology fit, and system usability.

The strength and direction of the correlation indicate a close association between human-related and technology-related dimensions of AI adoption. However, the result does not establish a causal relationship between the two subsystems.

Table 11

Significant relationship between the social subsystem and the technical subsystem in the adoption of AI

Variables	**Technical Subsystem**	
Correlation	r- value	p-value
Social Subsystem	.909**	.000
Interpretation	**Significant Relationship**	

**correlation is significant @ 0.01 level

The finding supports the Sociotechnical Systems (STS) perspective, which emphasizes the joint consideration of social and technical elements in organizational systems. Mumford (2006) emphasized the importance of balancing human and technological requirements in system implementation. Similarly, Brynjolfsson and McAfee (2014) noted that the benefits of digital technologies are enhanced when technological investments are accompanied by appropriate changes in organizational processes and workforce capabilities. Thus, the significant relationship observed in the present study reinforces the importance of considering both social and technical dimensions in AI adoption.

Adopting a holistic approach to AI implementation is important, where both social and technical subsystems are developed in tandem. Institutions should therefore invest not only in advanced AI technologies but also in employee training, engagement strategies, and role redesign initiatives to ensure sustainable and effective adoption.

Table 12

Significant relationship between the technical subsystem and the human–technology interface.

Variables	**Human-Technology Interface**	
Correlation	r- value	p-value
Technical Subsystem	.922**	.000
Interpretation	**Significant Relationship**	

**correlation is significant @ 0.01 level

Table 12 presents the relationship between the technical subsystem and the human–technology interface. The results show a very strong positive correlation ($r = 0.922$, $p < .001$), indicating a statistically significant relationship at the 0.01 level. This indicates that higher assessments of technical subsystem factors, including AI capability, task–technology fit, and system usability, are associated with higher assessments of human–AI collaboration quality and workflow integration. The technical characteristics are closely associated with how employees interact with and integrate AI systems into their work. In particular, reliable, usable, and task-appropriate technologies are associated with more favorable assessments of human–AI collaboration and workflow integration. However, the correlation does not establish a causal relationship between the variables.

The finding is consistent with Davis's (1989) TAM, which identifies perceived usefulness and perceived ease of use as important determinants of technology acceptance and use. It also supports Shneiderman's (2020) emphasis on human-centered design in promoting effective interaction with intelligent systems. Thus, the significant relationship observed in the study highlights the importance of technical capability, task alignment, and usability in supporting effective human–AI interaction and workflow integration.

Organizations need to prioritize the development of user-centered, reliable, and task-aligned AI systems. Investments in technical quality, particularly in usability and system design, do not merely improve system performance; they directly strengthen how employees engage with AI, ultimately leading to more effective adoption, greater efficiency, and stronger human–AI collaboration. Financing and lending institutions should adopt policies that promote responsible, human-centered, and agile AI integration, particularly as many institutions remain in the testing and partial-adoption stages.

First, strengthen AI governance and ethical standards. Institutions should establish clear policies on AI transparency, accountability, data privacy, and responsible use to ensure regulatory compliance and maintain customer trust (OECD, 2019). Second, develop human-centered AI systems. AI should augment rather than replace employees by supporting productivity and decision-making in areas such as credit assessment, fraud detection, customer service, and data management, while retaining human oversight for critical decisions (Davenport & Ronanki, 2018). Third, enhance workforce reskilling and AI readiness. Continuous training in AI literacy, digital competencies, and technology management should be provided to strengthen employee adaptability and address capability gaps associated with

AI-driven work transformation (World Economic Forum, 2020). Fourth, establish agile and adaptive work systems. Flexible workflows, collaborative decision-making, and continuous process improvement should be encouraged to enable employees and organizations to respond effectively to technological change (Brynjolfsson & McAfee, 2014). Finally, improve organizational efficiency and service delivery. Strategic AI integration should enhance operational efficiency, analytical accuracy, customer responsiveness, and risk management while maintaining quality human interaction (McKinsey Global Institute, 2017).

5. Conclusion

The study examined Artificial Intelligence (AI) adoption in selected financing and lending institutions in Cabanatuan City through the Sociotechnical Systems (STS) perspective. AI adoption was positively assessed in terms of redefinition of human roles, employee adaptation, and employee engagement. In addition, participants positively assessed AI capability, task–technology fit, and system usability. Meanwhile, human–AI collaboration quality and workflow integration both obtained a WM of 2.89 ("Agree"). AI was perceived to complement employee expertise, improve task efficiency, and support smoother workflow integration, demonstrating the importance of effective interaction between employees and AI-enabled systems.

A very strong and statistically significant positive relationships were found between the social and technical subsystems as well as technical subsystem and the human–technology interface. The findings support human-centered and agile AI policies emphasizing workforce reskilling, task-aligned and user-friendly technologies, workflow integration, ethical governance, and continued human oversight. These measures are particularly relevant because AI adoption remains at different stages among the participating institutions, with 35% reporting that adoption had not yet started and 21.67% reporting full integration. The findings provide a basis for further research on AI adoption in financing and lending institutions beyond Cabanatuan City.

The study is limited to 120 participants from 20 selected financing and lending institutions in Cabanatuan City using purposive–quota sampling. Therefore, the findings should not be generalized to all Philippine financing and lending institutions. The study also relied primarily on self-reported survey responses, which may be influenced by participants' perceptions and experiences. Furthermore, the descriptive-correlational design establishes relationships among variables but does not demonstrate causal effects. Future research should address these limitations through larger probability-based samples, longitudinal designs, and qualitative or mixed-method approaches.

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Institutional Review Board Statement

This study was conducted in accordance with the ethical guidelines set by Wesleyan University-Philippines. The conduct of this study has been approved and given relative clearance(s) by Wesleyan University-Philippines.

AI Declaration

The author declares the use of Artificial Intelligence (AI) in writing this paper. In particular, the author used Microsoft Copilot and ChatGPT in searching for appropriate literature, summarizing key points, restructuring language/sentences, and improving clarity. The author takes full responsibility in ensuring proper review and editing of content generated using AI.

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