Adoption Readiness to a Higher Level of Artificial Intelligence (AI)-Integrated Customer Support of a Customer Support Department in the Philippines

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Abstract: The adoption of Artificial Intelligence (AI), specifically in the Customer Support (CS) industry, is rapidly gaining traction to transform business models and improve customer service delivery. This study was motivated by the theory that there are three levels of AI intelligence used in service – Level 1 (Mechanical AI), Level 2 (Thinking AI), and Level 3 (Feeling AI). The subject company of this study was identified to be currently using Level 1 AI, which focuses purely on automation and rules. It has recently announced to gear towards the adoption of Level 2 AI, which should focus on using Generative AI to improve its services. The objective of this study was to assess the readiness of the CS department of the subject company to adopt a Level 2 AI-integrated CS. Using a quantitative method, the factors responsible for the successful adoption readiness of Level 2 AI were identified using a modified Artificial Intelligence Compensatory Level of Acceptance (AICLA) framework, which introduced three new constructs: AI Service Quality, AI Service Satisfaction, and AI Use Frequency. Using convenience sampling, data were gathered from 178 CS employees of the subject company through online survey questionnaire. Data were analyzed using partial least squares structural equation modelling (PLS-SEM) technique. The study provided empirical evidence on the factors responsible for the successful adoption of Level 2 AI. Results statistically revealed that Level 2 AI should provide a high guarantee of service satisfaction since it directly impacts the employees' perception of its intelligence and abilities to help them achieve their daily tasks, which also directly influences their readiness perception to adopt it. In general, Level 2 AI should be highly capable, be able to improve employees' productivity and performance, and be able to be thoroughly learned by employees through training.

Key Words: Artificial Intelligence; Customer Support; Adoption; Generative AI; Chatbot

1. INTRODUCTION

Technological innovation in Artificial Intelligence (AI) has fostered business transactions and services, driving organizations to develop new business models. Specifically in the customer support industry, the use of AI is rapidly gaining traction, with its applications ranging from frontline service interactions, to customer relationship management, to back-office processing activities (Huang et al., 2019). There are many definitions of AI but generally, scholars agree that it refers to computational agents that act intelligently to rapidly interpret and process a large quantity of data correctly, learn from such data, and use these learnings to reach specific goals and tasks (Ameen et al., 2021; Kaplan & Haenlein, 2019). A report by Accenture (2016, as cited in Buchholz, 2020) projected that AI technologies will increase business productivity by up to 40% by 2035. There is an immense opportunity in adopting AI, hence, factors responsible for the successful implementation of it must be identified.

This study was motivated by Huang and Rust (2021)'s theory and framework that posits there are three levels of AI intelligence. According to them, there are three levels of AI used in service that can be used differentially to engage customers – mechanical, thinking, and feeling. Level 1 is Mechanical AI. Mechanical AI is the lowest level of AI intelligence and is currently the most common level of AI and have various practical applications. Mechanical AI concerns the ability to automatically perform routine, repeated tasks. Examples of this type of AI include self-service technologies and rule-based chatbots. On the other hand, Level 2 is Thinking AI, which is a higher level of AI intelligence. It is currently a mainstream research and application focus. Thinking AI learns and adapts from data which demonstrates analytical or intuitive abilities. Thinking AI iteratively learns from data and identifies meaningful patterns. It also has the ability to think creatively and adjust depending on the context. Examples of this type of AI include predictive analytics, data mining, machine/deep learning, and generative AI. The highest level, Level 3 is Feeling AI, which is at its early stages of development and far from most practical applications. This type of intelligence has the ability to recognize emotions and can react empathetically with users. Examples of such are speech emotion recognition, sentiment analysis, and advanced robots.

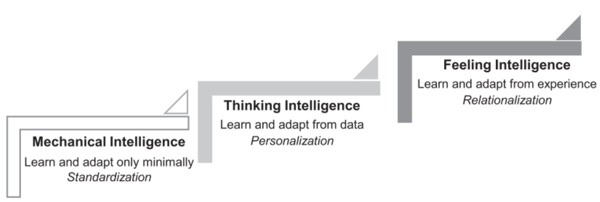

Fig 1. Three Levels of AI used in Service

AI-integrated customer support (CS) is the customer service delivery through automations trained by AI, machine learning (ML), and other advancements in technology.

The subject company in this study is a cloud-based enterprise software company that provides Enterprise Resource Planning (ERP) solution. It also provides support services, driven by its Customer (CS) Department, with technical support engineers across the globe, delivering post-go-live support to customers, from online case submissions to 24x7 phone support. Currently, the CS department of the subject company is using Level 1 AI through its rule-based chatbot. However, it has identified gaps including low success/resolution rate and low customer satisfaction rate. The subject company also announced that is gearing towards the adoption of Generative AI, which is categorized as a Level 2 AI, to improve the current rule-based chatbot into an advanced, conversational, AI-based chatbot. Level 2 AI, such as generative AI, can also help technical support engineers increase productivity by authoring responses to service requests, which could be further enabled by assisted agent responses, assisted knowledge articles, search augmentation, customer engagement summaries, assisted guidance authoring, and field service recommendations, all of which should address the gaps identified in using Level 1 AI.

The subject company is at its early stages of adopting a Level 2 AI and the successful implementation of it will depend on the employees' expertise and willingness to implement, maintain, and adopt such technology. Their perceptions must be aligned to support the system, hence, the factors impacting their perceptions and readiness to use Level 2 AI must be identified (Chatterjee et al., 2021). Following this, the general objective of this study was to assess the readiness of the CS department of the subject company to adopting a Level 2 AI-integrated CS. This was carried out using the following specific objectives:

- To develop an adoption readiness framework and develop hypotheses that will be used as a basis of the questions in the measurement instrument.
- To evaluate the adoption readiness framework by conducting a survey to the CS department of the subject company.
- To analyze the data gathered from the CS department to validate the hypotheses formulated.

- To draw conclusion and recommendations on how the CS department can be ready to adopt a Level 2 AI-integrated CS.

To evaluate the adoption readiness, this study proposed an adoption readiness framework which is a modified version of the Artificial Intelligence Compensatory Level of Acceptance (AICLA) framework introduced by Sau et al. (2023). The AICLA framework was modified to be applied specifically to Level 2 AI instead of a generic AI service and to be applied to a customer support department. This study introduced three new constructs: AI Service Quality, AI Service Satisfaction, and AI Use Frequency.

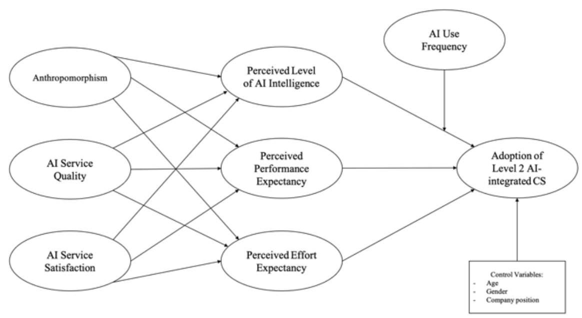

Fig 2. The Proposed Adoption Readiness Framework

The proposed adoption readiness framework has the following constructs: Anthropomorphism (ANTHRO), AI Service Quality (QUAL), AI Service Satisfaction (SAT), Perceived Level of AI Intelligence (LAII), Perceived Performance Expectancy (PE), and Perceived Effort Expectancy (EE), and AI Use Frequency (FREQ) as the introduced moderating variable.

2. METHODOLOGY

This study employed a quantitative method to empirically validate the proposed adoption readiness framework and carried out using Sepasgozar and Davis (2018)'s research methodology on technology adoption which consists of three main phases – technology investigation, framework development, and framework evaluation phase.

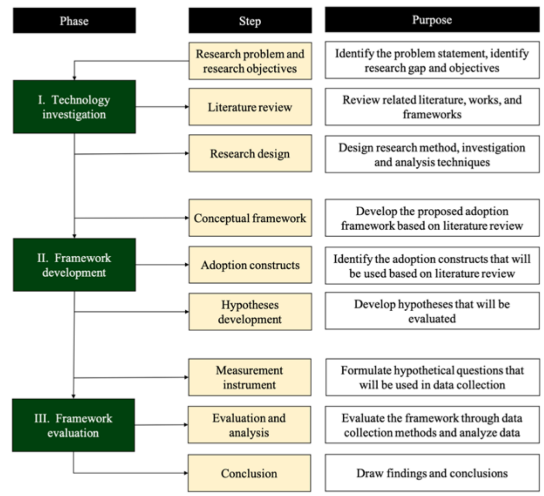

Fig 3. Research Methodology

Data collection method was in the form of survey questionnaire administered online to the CS employees of the subject company. This study used convenience sampling and data analysis used a partial least squares structural equation modelling (PLS-SEM) technique. PLS-SEM was used to identify the relationships among the constructs in order to predict if CS department are likely to be ready to adopt a Level 2 AI-integrated CS.

2.1. Technology Investigation Phase

In this phase, the research problem was identified, as well as the research questions and research objectives, which built the foundation of this study.

2.2. Framework Development Phase

In this phase, the proposed adoption framework was designed, which is the conceptual framework in this study. A new set of constructs were adapted from previous AI adoption studies and hypotheses were formulated based on the review of existing literature. The hypotheses formulated are summarized in Table 1.

Tab 1. Hypotheses Development

No.	Path	Description
H1	ANTHRO+ → LAII	Anthropomorphism has a positive influence on the perceived level of AI intelligence
H2	ANTHRO+ → PE	Anthropomorphism has a positive influence on the perceived performance expectancy
H3	ANTHRO- → EE	Anthropomorphism has a negative influence on the perceived effort expectancy
H4	QUAL+ → LAII	AI service quality has a positive influence on the perceived level of AI intelligence
H5	QUAL+ → PE	AI service quality has a positive influence on the perceived performance expectancy
H6	QUAL- → EE	AI service quality has a negative influence on the perceived effort expectancy
H7	SAT+ → LAII	AI service satisfaction has a positive influence on the perceived level of AI intelligence
H8	SAT+ → PE	AI service satisfaction has a positive influence on the perceived performance expectancy
H9	SAT+ → EE	AI service satisfaction has a positive influence on the effort performance expectancy
H10	LAII+ → ADOP	Perceived level of AI intelligence has a positive influence on the adoption of Level 2 AI-integrated CS
H11	PE+ → ADOP	Perceived performance expectancy has a positive influence on the adoption of Level 2 AI-integrated CS
H12	EE- → ADOP	Perceived effort expectancy has a negative influence on the adoption of Level 2 AI-integrated CS
H13	FREQ+ * LAII → ADOP	AI use frequency has a positive influence on the effect of the perceived level of AI intelligence on the adoption of Level 2 AI-integrated CS

2.3. Framework Evaluation Phase

Finally, the proposed adoption framework was tested in this phase. Hypothetical survey questions were formulated based on adapted questions from previous studies and research-made questions in order to build the research instrument. The survey questionnaire was validated through expert validation and pilot testing of a small population of N=34 and was confirmed to be reliable and valid.

3. RESULTS AND DISCUSSION

A total of N=178 respondents participated in this study. More than half of the respondents were aged between 20 and 29 years old (56.18%), followed by respondents aged between 30 and 39 years old (32.58%). Meanwhile, 53.37% of the respondents were male while 46.63% were female. In terms of their company position, 68.54% of the respondents were individual contributors while 31.46% were in leadership/managerial roles. The data also showed that the majority of the respondents are familiar with AI (81.46%) and majority of them have used AI in the form of chatbots and generative AI.

In order to ensure reliability and validity, data gathered from the survey were inputted to SmartPLS for calculation, validation, and analysis. SmartPLS is a data analysis software used for structural equation modeling (SEM) analysis. Reliability is presented through internal consistency by calculating Cronbach's alpha coefficient and through composite reliability. On the other hand, validity is presented through factor loading analysis and average variance extracted (AVE) to measure convergent validity and through heterotrait-monotrait (HTMT) ratio to measure discriminant validity. The results are summarized in Table 2.

Table 2. Measurement Quality

Construct	Cronbach's alpha	Composite Reliability	AVE
ANTHRO	0.703	0.735	0.494
QUAL	0.733	0.796	0.521
SAT	0.883	0.886	0.604
LAII	0.748	0.785	0.512
PE	0.744	0.839	0.593
EE	0.777	0.812	0.578
FREQ	0.741	0.821	0.519
ADOP	0.898	0.901	0.683

Path relationships were analyzed using the same data set through SmartPLS Bootsrapping. Path analysis is used to uncover the interrelationships among constructs and is represented through a path diagram and path coefficient values are represented by ß. Testing the hypotheses formulated in this study also produces a p-value for each path coefficient. p is the value of probability. A p-value < 0.05 is considered to be statistically significant, meaning there is strong evidence or relationship between the constructs. Conversely, a p-value > 0.05 or close to 1 is considered not statistically significant.

Table 3. Hypotheses, Path Coefficients, and p-values

No.	Path	Path Coefficient	p-value	Significance	Hypothesis supported?
H1	ANTHRO+ → LAII	0.188	0.048	*	supported
H2	ANTHRO+ → PE	0.211	0.032	*	supported
H3	ANTHRO- → EE	-0.038	0.045	*	supported
H4	QUAL+ → LAII	0.298	0.038	*	supported
H5	QUAL+ → PE	0.169	0.005	**	supported
H6	QUAL- → EE	0.522	0.068	ns	not supported
H7	SAT+ → LAII	0.576	0	***	supported
H8	SAT+ → PE	0.575	0	***	supported
H9	SAT+ → EE	0.277	0.003	**	supported
H10	LAII+ → ADOP	0.696	0.027	*	supported
H11	PE+ → ADOP	0.24	0.039	*	supported
H12	EE- → ADOP	-0.033	0.044	*	supported
H13	FREQ+ * LAII → ADOP	0.149	0.032	*	supported

Note: p-value: ***p<0.001, **p<0.01, *p<0.05, ns: not significant

All hypotheses formulated in this study were supported except for H6. This study found that ANTHRO has a positive and significant influence on both LAII (ß = 0.188, p < 0.05), and PE (ß = 0.21, p < 0.05) and a negative and significant influence on EE (ß = -0.038, p < 0.05), providing support to H1, H2, and H3. On the other hand, QUAL was also found to have a positive and significant influence on LAII (ß = 0.298, p < 0.05) providing support for H4. H5 was also found to be supported with QUAL having a positive and significant influence on PE (ß = 0.169, p < 0.01). H7, H8, and H9 are found to be supported as well with SAT having a positive and significant influence on LAII (ß = 0.576, p < 0.001), on PE (ß = 0.575, p < 0.001), and EE (ß = 0.277, p < 0.01). In addition, it was found out that LAII has a positive and significant influence on ADOP (ß = 0.696, p < 0.05) which supports H10. PE also has a positive and significant influence on ADOP (ß = 0.24, p < 0.05), supporting H11. EE on the other hand, has a negative and significant influence on ADOP (ß = -0.033, p < 0.05). Finally, both FREQ and LAII was found to have a positive and significant influence on ADOP (ß = 0.149, p < 0.05), supporting H13.

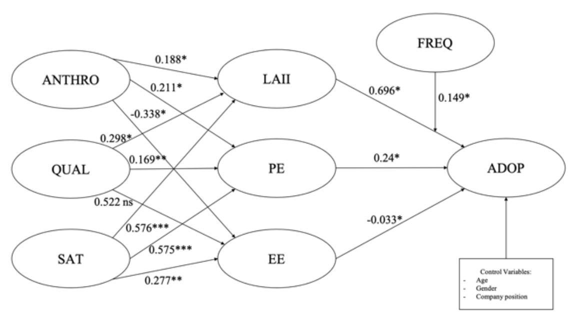

Fig 4. The Proposed Adoption Readiness Framework with Empirical Results

4. CONCLUSIONS

This study was able to provide an extensive micro-analysis of not just AI adoption in general but instead it viewed it through the lens of Huang and Rust (2021)'s theory of three levels of AI. This study specifically focused on the adoption readiness to Level 2 AI, which is a higher level of AI intelligence and has a lot of opportunities for research and most practical applications. Through a comprehensive literature review, this study introduced a new framework, which is a modified AICLA framework, designed to be applicable to Level 2 AI and CS departments. This study also introduced three new constructs in AI adoption: AI Service Quality, AI Service Satisfaction, and AI Use Frequency.

In theory, this study was able to provide empirical evidence of the factors responsible for adoption readiness of Level 2 AI-integrated CS. The most significant finding of this study is that the AI Service Quality has a very significant influence to the Perceived Level of AI Intelligence and to the Perceived Performance Expectancy. The rest of the hypotheses formulated were generally validated and provided evidence how customer support employees are likely to be ready to adopt Level 2 AI.

In practice, this study implies that customer support leaders should not just blindly invest and adopt Level 2 AI but consider factors on the successful AI adoption. This study highlights that leaders should ensure a high guarantee of service satisfaction provided by Level 2 AI since it directly impacts the employees' perception of its intelligence and abilities to help them achieve their daily tasks, which also directly influences their readiness perception to adopt it. This study also highlights the importance of experience and familiarity with using AI. If employees already have a familiarity using AI and they have an understanding of its capabilities, it directly influences their readiness perception to adopt it. Lastly, leaders must consider Level 2 AI to be highly capable, to be able to improve employees' productivity and performance, and to be able to be thoroughly learned by employees through training. All of these were statistically validated to directly affect their readiness to adopt Level 2 AI in customer support operations.

There are a few limitations in this study and there are recommendations for future research. This study was only limited to N=178 employees from the Philippines and was conducted within a relatively short amount of time. There could be cultural factors that might have affected the results. Hence, future research may conduct a longitudinal study with a greater number of participants from different areas of CS operations globally. Future research may also explore other constructs, such as the employees' social influence and self-concept, which could better predict their readiness to adopt.

5. ACKNOWLEDGMENTS

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