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Determinants of Behavioral Intention to Use Ai in Business Operations among Multipurpose Cooperatives: A Structural Equation Model

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Abstract

Artificial Intelligence (AI) is increasingly recognized as a strategic tool for enhancing organizational efficiency, innovation, and decision-making. This study examined the factors influencing the behavioral intention to use AI among decision-makers of multipurpose cooperatives in the Davao Region, focusing on the Unified Theory of Acceptance and Use of Technology (UTAUT) Model, Personal Concern, Perceived Risk, and Top Management Support. Using a quantitative approach through Pearson correlation, ordinary least squares regression, and partial least squares structural equation modeling (PLS-SEM), the study found that all constructs were rated high and significantly related to behavioral intention. The results revealed that the UTAUT Model was the strongest predictor of behavioral intention, followed by Personal Concern and Top Management Support, while Perceived Risk had no significant influence. The model demonstrated strong explanatory and predictive capability, confirming that AI adoption among cooperatives is primarily driven by perceived usefulness, ease of use, social influence, organizational support, and personal considerations. The findings reinforce the applicability of the UTAUT framework in explaining AI acceptance and provide insights for promoting AI adoption and digital transformation in cooperative organizations.

Keywords: business administration, artificial intelligence (AI), behavioral intention, Unified Theory of Acceptance and Use of Technology (UTAUT) model, multipurpose cooperatives, Partial Least Squares Structural Equation Modeling (PLS-SEM), Davao Region.

1. INTRODUCTION

Artificial Intelligence (AI) has emerged as a critical driver of organizational transformation, redefining how businesses plan, operate, and sustain competitive advantage (Duan, Edwards, and Dwivedi, 2019). Globally, AI technologies are increasingly utilized for predictive analytics, automation of routine processes, customer engagement, fraud detection, and strategic decision-making. International organizations and scholars emphasize that AI adoption is no longer optional but a strategic necessity for organizational resilience and long-term sustainability (Dwivedi, Hughes, Ismagilova, Aarts, Coombs, Crick, Duan, Edwards, Eirug, 2021).

Despite these developments, the adoption and continued use of AI in business operations remain uneven, particularly among cooperative enterprises in developing economies (Sousa, Pani, Dal Mas, & Sousa, 2024). In the Philippines, multipurpose cooperatives play a vital socio-economic role by providing financial services, livelihood support, and community development initiatives. However, many cooperatives operate with resource constraints, collective decision-making structures, and heightened risk sensitivity, which may hinder their readiness and willingness to adopt AI-driven systems (Venkatesh, Thong and Xu, 2022).

The central issue addressed in this study is behavioral intention to use AI, defined as the degree to which organizational decision-makers are willing to adopt, continue, and expand the use of AI technologies in their operations. While digital tools are increasingly accessible, empirical evidence shows that availability does not automatically translate into actual or sustained use (Venkatesh et al., 2022). Behavioral intention thus becomes a critical explanatory construct in understanding AI adoption outcomes.

Besides, businesses are increasingly turning to AI for reliable outcomes, implying that companies planning to adopt AI must incentivize their staff to use it (Chatterjee, Chaudhuri, Vrontis, Thrassou, and Ghosh, 2021). Nonetheless, it demands an examination of the manager's usage behavior. To figure out how managers use AI, their attitudes and intentions need to be in line with how they want to use the system, because their goals and attitudes are what make people do what they do. Managers who are responsible for evaluating consumer data must utilize AI (Chatterjee, Rana, Khorana, Mikalef, and Sharma, 2021). Such technologies assist businesses incorrectly analyzing their consumers' preferences, habits, and dislikes (Chatterjee, Chaudhuri, Vrontis, Thrassou, and Ghosh, 2021).

Meanwhile, the growing adoption of artificial intelligence (AI) in business operations has reshaped decision-making, efficiency, and competitive advantage across industries, making the study of behavioral intention to use AI increasingly important. Prior research consistently emphasizes that AI adoption is not solely a technological issue but a behavioral and organizational phenomenon influenced by users' expectations, perceptions, and contextual conditions. Models such as the Unified Theory of Acceptance and Use of Technology (UTAUT) remain central in explaining AI adoption, with empirical studies demonstrating that performance expectancy, effort expectancy, facilitating conditions, and social influence significantly affect users' intention to adopt AI-based systems (Venkatesh et al., 2020; Dwivedi et al., 2021). However, recent literature also underscores that in complex organizational environments, particularly among decision makers and leaders, behavioral intention is shaped by broader concerns, including perceived risks, personal values, and managerial support. This is especially relevant in cooperative organizations, where leaders must balance technological innovation with financial sustainability, member trust, and social responsibility.

Existing studies further contribute by highlighting the role of personal concerns, perceived risk, and top management support as critical determinants of AI adoption, yet these factors are often examined in isolation or within corporate and technologically advanced contexts. Research indicates that concerns about personal development and well-being influence leaders' openness to AI, as fears of skill obsolescence, increased stress, or loss of professional autonomy may reduce intentions to adopt AI (Raisch & Krakowski, 2021; Tarafdar et al., 2020). Similarly, perceived financial, security, performance, social, and psychological risks have been found to significantly dampen behavioral intention, particularly in settings with limited resources and high accountability (Marikyan et al., 2022; Zhang et al., 2021). At the organizational level, top management support through resource provision, structural arrangements, communication, expertise, and decision power has been shown to mitigate risk perceptions and strengthen adoption intentions (Bag et al., 2021; Verhoef et al., 2021). Despite these contributions, there remains a notable gap in empirical research on decision-makers and leaders of multipurpose cooperatives, particularly in developing regions such as the Davao Region. This gap justifies the purpose of the present study: to develop and test a structural equation model that integrates UTAUT factors, personal concerns, perceived risk, and top management support to explain behavioral intention to use AI captured through actual and future use in cooperative business operations.

The relationship between the independent variables and behavioral intention to use AI is well established in contemporary technology adoption literature, particularly in organizational decision-making contexts. Empirical studies consistently show that UTAUT factors, performance expectancy, effort expectancy, facilitating conditions, and social influence exert a direct and significant influence on users' intention to adopt AI systems, as these variables capture both perceived utility and contextual readiness for technology use (Venkatesh et al., 2020; Dwivedi et al., 2021). In parallel, recent research extends beyond purely technological determinants by demonstrating that personal concerns, including personal development and well-being, shape leaders' willingness to engage with AI, especially when adoption is perceived to threaten professional growth, autonomy, or work-life balance (Raisch & Krakowski, 2021; Tarafdar et al., 2020). Moreover, perceived risk, encompassing financial, security, performance, social, and psychological dimensions, has been shown to negatively correlate with behavioral intention, particularly among organizational leaders responsible for financial sustainability, data integrity, and stakeholder trust (Marikyan et al., 2022; Zhang et al., 2021). Conversely, top management support strengthens behavioral intention by providing resources, structural arrangements, communication, expertise, and decision-making power, thereby reducing uncertainty and legitimizing AI adoption initiatives within organizations (Bag et al., 2021; Verhoef et al., 2021).

The anchored theory explaining the interrelationship between the independent variables and the dependent variable in this study is the Unified Theory of Acceptance and Use of Technology (UTAUT). UTAUT posits that behavioral intention is a function of users' expectations of performance gains, ease of use, organizational and technical support, and social pressures within the environment (Venkatesh et al., 2020). In the context of AI adoption in business operations, UTAUT provides a robust explanatory foundation by capturing both individual cognitive evaluations and organizational conditions influencing intention to use. However, as AI systems introduce greater complexity, autonomy, and uncertainty than traditional information systems, scholars increasingly argue that UTAUT must be extended to incorporate risk perceptions, personal concerns, and leadership dynamics to remain theoretically and empirically relevant (Dwivedi et al., 2021).

Supporting this anchor theory are three complementary theoretical perspectives. First, Perceived Risk Theory explains how uncertainty and potential negative consequences reduce individuals' willingness to adopt innovations, particularly when financial loss, security breaches, performance failure, or psychological discomfort are salient (Marikyan et al., 2022). Second, Human Capital Theory supports the inclusion of personal development concern by suggesting that individuals evaluate technologies based on their perceived impact on skills, career progression, and long-term professional value, which directly influences adoption intention (Raisch & Krakowski, 2021). Third, the Top Management Support Model, often embedded in organizational change and innovation diffusion frameworks, posits that leadership commitment, resource allocation, and authoritative support are critical enablers of technology acceptance, especially in structured and member-driven organizations such as cooperatives (Bag et al., 2021). Together, these theories explain how technological perceptions, personal evaluations, risk assessments, and organizational leadership interact to shape behavioral intention to use AI.

From a personal scholarly standpoint, the integration of UTAUT with perceived risk, personal concern, and top management support is particularly compelling in the context of multipurpose cooperatives in the Davao Region, where decision makers operate under conditions of limited resources, high accountability to members, and strong social embeddedness. Unlike in corporate settings, cooperative leaders must justify AI adoption not only on efficiency grounds but also on financial prudence, member welfare, and organizational values. As such, behavioral intention to use AI cannot be adequately explained by performance and effort expectations alone. The present study advances existing literature by positioning behavioral intention as a multidimensional construct shaped by rational evaluation, emotional concern, perceived vulnerability, and leadership endorsement. By empirically testing these relationships using a structural equation model, this research contributes a context-sensitive and theoretically enriched understanding of AI adoption among cooperative leaders, addressing a significant gap in both the AI and cooperative management literatures.

This research has two main variables: exogenous and endogenous constructs. The exogenous constructs are the UTAUT model (Venkatesh et al., 2003), personal concern (Cao et al., 2021), perceived risk (Liang et al., 2018), and top management support (Ahmed & Azmi bin Mohamed, 2017). In contrast, the endogenous construct is behavioral intention (Brezavšček et al., 2017).

The first variable explored in the study is the UTAUT model. The Unified Theory of Acceptance and Use of Technology (UTAUT) is widely used to explain technology adoption and behavioral intention. It posits that individuals' intention to use technology is determined by four key indicators: performance expectancy, which reflects the degree to which a person believes that using AI will improve job performance; effort expectancy, or the perceived ease of using AI systems; facilitating conditions, referring to organizational and technical infrastructure that supports AI use; and social influence, which captures the extent to which peers, supervisors, or the organizational environment encourage adoption (Venkatesh et al., 2020; Dwivedi et al., 2021). Prior studies have confirmed the significant influence of UTAUT indicators on behavioral intention across various organizational contexts, including SMEs and cooperative settings, demonstrating the framework's reliability for understanding AI adoption (Dwivedi et al., 2021).

The second variable is personal concern. This variable captures an individual's perceptions about how technology adoption affects their personal development and well-being. Its indicators are personal development concerns, which relate to the fear of skills obsolescence or reduced professional growth due to AI integration, and personal well-being concerns, which reflect apprehension regarding stress, work-life balance, or job satisfaction (Raisch & Krakowski, 2021; Tarafdar et al., 2020). Studies indicate that personal concerns can moderate or directly influence behavioral intention to use technology, as individuals may hesitate to adopt AI if it threatens their career trajectory or emotional well-being (Cao et al., 2021).

The third variable is perceived risk. Perceived risk refers to the potential negative consequences of using AI in business operations. It comprises five indicators: financial risk, which concerns potential monetary losses; security risk, related to data breaches or unauthorized access; performance risk, reflecting concerns about AI's effectiveness; social risk, which refers to potential reputation or relational impacts; and psychological risk, which involves stress or anxiety induced by using AI systems (Marikyan et al., 2022; Zhang et al., 2021). Research shows that higher perceived risks significantly reduce behavioral intention to use AI, particularly among leaders and decision makers who are accountable for both organizational outcomes and stakeholder trust (Liang et al., 2018).

The fourth variable is top management support. This organizational factor is essential in facilitating AI adoption. Its indicators include provision of resources, structural arrangements that integrate AI into operations, communication that informs and motivates users, expertise in managing AI technologies, and decision-making power to authorize adoption initiatives (Bag et al., 2021; Verhoef et al., 2021). Studies consistently demonstrate that top management support enhances employees' behavioral intention to use AI by providing both practical support and legitimization within the organization (Ahmed & Azmi bin Mohamed, 2017).

The dependent variable of the study is behavioral intention to use AI. Behavioral intention reflects the readiness or willingness of individuals to use AI systems in business operations. Its indicators are actual use, referring to the present engagement with AI tools, and future use, representing the intention to adopt AI-based solutions in subsequent organizational processes (Brezavšček et al., 2017). The behavioral intention construct is central to technology adoption studies because it serves as a proximal predictor of actual system usage, bridging perceptions, attitudes, and eventual behavioral outcomes.

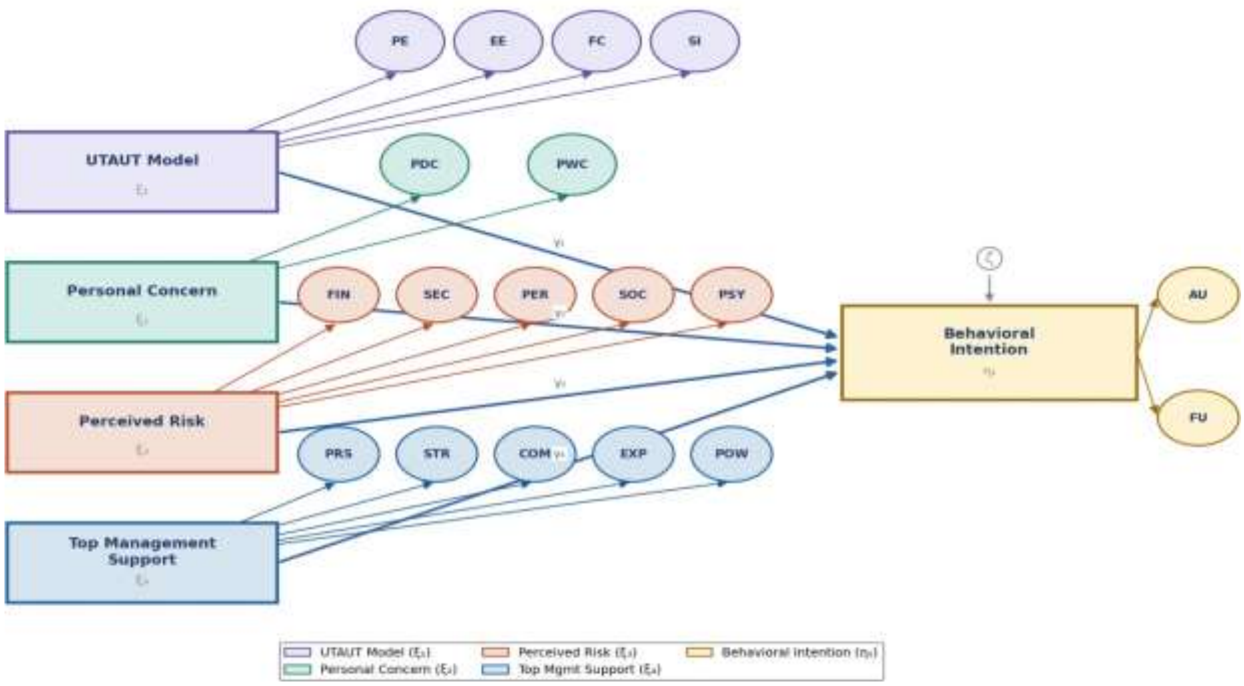

Figure 1. Conceptual Path Diagram of the Proposed PLS-SEM Model

LEGEND:	
UNIFIED THEORY OF ACCEPTANCE AND USE OF TECHNOLOGY	**TOP MANAGEMENT SUPPORT**
PE - Performance Expectancy	PRS - Provide Resources
EE - Effort Expectancy	STR – Structural Arrangements
FC - Facilitating Condition	COM - Communication
SI - Social Influence	EXP - Expertise
	POW - Power
PERSONAL CONCERN	**PERCEIVED RISK**
PWC – Personal Wellbeing Concern	FIN - Financial Risk

PDC – Personal Development Concern	SEC - Security Risk
BEHAVIORAL INTENTION	PER - Performance Risk
AU – Actual Use	SOC - Social Risk
FU – Future Use	PSY - Psychological Risk

Figure 1 depicts the proposed structural model of the study. The proposed structural model was developed based on the Unified Theory of Acceptance and Use of Technology (UTAUT) and complementary theoretical constructs to examine the hypothesized relationships among the UTAUT Model, Personal Concern, Perceived Risk, Top Management Support, and Behavioral Intention to use Artificial Intelligence (AI) among multipurpose cooperatives. The model's findings are intended to provide empirical evidence to guide the development of organizational strategies, programs, and policies to enhance AI adoption among multipurpose cooperatives.

Specifically, the study examined the levels of the UTAUT Model (UM), Personal Concern (PC), Perceived Risk (PR), Top Management Support (TMS), and Behavioral Intention (BI). It also examined the relationships among these latent constructs and evaluated the direct effects of the exogenous constructs on Behavioral Intention using Partial Least Squares Structural Equation Modeling (PLS-SEM). The proposed model will be evaluated using Partial Least Squares Structural Equation Modeling (PLS-SEM) to assess the hypothesized relationships among the study constructs. The hypotheses of the study were tested at the 0.05 level of significance.

Furthermore, this study aligns with Sustainable Development Goal (SDG) 8 (Decent Work and Economic Growth) by exploring how AI adoption can enhance efficiency, innovation, and economic growth within cooperatives. By understanding and addressing the factors influencing AI adoption, cooperatives can enhance their operations, create new opportunities for decent work, and foster sustainable economic growth. The integration of AI has the potential to improve decision-making, optimize resource allocation, and increase productivity, all of which contribute to the goals of inclusive and sustainable economic development.

It is worth noting that the Cooperative Development Authority Region XI emphasized that, amidst evolving technological landscapes, committees should remain objective and committed to monitoring AI adoption initiatives (CDA-Davao Region, 2022). Thus, the study's results strongly support the continued promotion of AI within multipurpose cooperatives, whose decision-makers play a critical role in driving organizational adoption. Beyond cooperatives, other sectors such as small and medium enterprises, agribusiness, and service-oriented organizations stand to benefit from increased behavioral intention to use AI, as it can enhance operational efficiency, improve decision-making, and strengthen customer service. The findings provide guidance for organizational leaders in implementing AI strategies, addressing perceived risks, and leveraging technological, personal, and managerial factors to foster a culture of AI adoption. Additionally, the study equips cooperative leaders with insights to develop effective strategies that align AI adoption with organizational goals, member needs, and sustainable growth.

Lastly, this study allowed future researchers to examine other related variables and how this affects multipurpose cooperatives' BI to use AI. It remarks its significance for giving the base to plan and making a practical framework; and building up a pioneering society, which drives abundance creation and provides a further push to development in various kinds of monetary circumstances or business.

2. METHODS

This chapter presents the discussion on the research design, research locale, population and sample, research instrument, data collection, and statistical tools.

Research Respondents

The respondents of this study were cooperative officers, managers, members, decision-makers, and representatives from registered multipurpose cooperatives in Region XI. A total of 424 respondents participated in the study. The sample size was considered adequate for Partial Least Squares Structural Equation Modeling (PLS-SEM). According to Hair et al. (2022), the adequacy of the sample size in PLS-SEM depends on the complexity of the structural model, the number of indicators measuring each latent construct, and the desired level of statistical power. The final sample of 424 respondents exceeded the recommended minimum sample size for PLS-SEM and was considered sufficient for estimating the proposed structural model and testing the hypothesized relationships among the study constructs. Likewise, Wolf et al. (2015) emphasized that larger sample sizes improve the stability of parameter estimates and increase the statistical power of structural equation models.

A combination of cluster sampling and simple random sampling was employed in selecting the respondents. Cluster sampling was first used because the target population was geographically distributed across the five provinces of Region XI. The registered multipurpose cooperatives were grouped according to province, with Cluster 1 representing Davao de Oro, Cluster 2 representing Davao del Norte, Cluster 3 representing Davao del Sur, Cluster 4 representing Davao Oriental, and Cluster 5 representing Davao Occidental. According to Thomas (2022), cluster sampling is an appropriate probability sampling technique for studying large, geographically dispersed populations.

After establishing the clusters, simple random sampling was employed within each province to select the participating cooperatives and their qualified respondents. This sampling procedure ensured that every eligible respondent in each cluster had an equal probability of selection, thereby minimizing selection bias and improving the representativeness of the sample.

Following the identification of the clusters, the researcher selected at least four registered multipurpose cooperatives in each province from which respondents would be drawn. However, only multipurpose cooperatives that granted permission to conduct the study were included in the sampling frame. For clusters with more than four approved cooperatives, the researcher employed the Randomizer online tool (https://www.randomizer.org/) to randomly select the participating cooperatives, thereby minimizing selection bias. According to Adwork (2015), simple random sampling may be conducted using several techniques, including random number tables, lottery methods, or computer-generated randomization algorithms. Conversely, for clusters with fewer than four approved cooperatives, all multipurpose cooperatives that permitted the study to be conducted were automatically included as participating cooperatives (Thomas, 2022).

After the participating cooperatives had been identified, the researcher selected the respondents using simple random sampling. This probability sampling technique was chosen because it provides every eligible member of the target population with an equal opportunity of being selected, thereby minimizing selection bias and enhancing the representativeness of the sample (Thomas, 2022). The respondents consisted of cooperative officers, managers, members, decision-makers, and representatives who were directly involved in technology adoption and organizational decision-making within the selected multipurpose cooperatives

Accordingly, the required sample size was determined using Cochran's formula, as the exact number of eligible respondents across all participating cooperatives could not be established because most cooperatives were unable to provide complete and updated lists of their officers, managers, members, decision-makers, and representatives. The population therefore consisted of individuals who were directly involved in technology adoption and organizational decision-making, while cooperative members not performing these functions were excluded from the study. The final sample comprised 424 respondents, which exceeded the minimum sample size recommended for structural equation modeling. Wolf et al. (2015) emphasized that adequate sample size contributes to more stable parameter estimates and improved statistical power. Similarly, Yuan and Chan (2016) and Yuan, Wu, and Bentler (2010) recommended sample sizes ranging from 300 to 400 respondents for structural equation modeling. Moreover, Hair et al. (2022) explained that the adequacy of the sample size in Partial Least Squares Structural Equation Modeling (PLS-SEM) depends on factors such as model complexity, the number of indicators, and the desired statistical power. Therefore, the final sample size of 424 respondents was considered sufficient for evaluating the proposed measurement model and structural model using PLS-SEM.

Materials and Instruments

This study used adapted and modified survey questionnaires for the five variables: UTAUT Model (Unified Theory of Acceptance and Use of Technology Model), Per Con (Personal Concern), Per Ris (Perceived Risk), ToM Sup (Top Management Support), and Beh Int (Behavioral Intention). The questionnaire content was adapted to the respondents' context; only relevant topics were included. Next, the adviser checked the questionnaire for comments and suggestions. The adapted questionnaire was first reviewed by the research adviser for content relevance, clarity, and consistency with the study's objectives. It was subsequently evaluated by four internal experts and one external validator. Based on their assessments, the instrument obtained an overall validation rating of 4.75, interpreted as Very Good, indicating that the questionnaire possessed satisfactory content validity prior to data collection. All constructs in the questionnaire were operationalized as reflective latent constructs and measured using multiple indicators adapted from previously validated instruments.

The research questionnaire was composed of five parts. Part I examined the respondents' UTAUT Model; Part II examined the respondents' personal concern; Part III examined the respondents' perceived risk; Part IV examined the respondents' top management support; and Part V examined the respondents' behavioral intention to use AI. All parts of the questionnaires comprised the indicators of each variable discussed in the underpinnings of this study's theoretical and conceptual frameworks. The first part of the questionnaire assessed the respondents' UTAUT Model (UM) in terms of four (4) subscales: performance expectancy, effort expectancy, facilitating conditions and social influence. Each indicator had five items/questions, for a total of 20 items/questions in the UTAUT Model questionnaire, which was adopted from Venkatesh et al. (2003). The second part measured the respondents' personal concern (PC) in two subscales: personal development concern and personal well-being concern. Each indicator had four to six items, for a total of 10 questions, which were adopted from the study by Cao et al. (2021). The third part of the survey evaluated the respondents' perceived risk (PR). Five indicators were used: financial risk, security risk, performance risk, social risk, and psychological risk, with 4 items or questions per indicator. The 20-item perceived risk questionnaire of Liang et. al. (2018) was adopted. The fourth part of the questionnaire measured top management support (TMS) across 5 subscales: providing resources, structural arrangements, communication, expertise, and power. Each indicator had five to six items, for a total of 26 questions, which were adopted from the study by Ahmed & Azmi bin Mohamed (2017). The last part of the questionnaire adopted Brezavšček et al., 8-item behavioral intention questionnaire (2017). The respondent's behavioral intention (BI) was measured for both actual and future use. Each indicator has 4-item questions.

The 5-item Likert scale was used to interpret the participants' responses: First, when the range of means is 1.00 to 1.79, it is described as very low, indicating that the variables are not manifest. Second, when the range of means is 1.80 to 2.59, it is described as low, indicating that the variables are rarely observed. Third, when the mean is within 2.60 to 3.39, the measures of the variables are sometimes manifested. Fourth, when the mean is within the range of 3.40 to 4.19, it indicates a high level and is interpreted as frequently manifested. Fifth, when it is within the range of 4.20 to 5.00, or very high, it specifies that the variables are always manifested.

Further, the questionnaire was pilot tested to 30 sample respondents. This step is done to ensure reliability and validity, as Nunnally and Bernstein (1994) stated that one must aim for reliability values of 0.70 or higher, or acceptable, using Cronbach's alpha. According to Conroy (2015), in pilot testing, at least 30 respondents or samples. Furthermore, all items in the survey had Cronbach's alpha values above 0.7.

On the other hand, Hair et al. (2016) provided the following rules of thumb for interpreting Cronbach's alpha; in this case, it is considered very good. The Cronbach's alpha for personal concern is 0.91, for behavioral intention 0.92, for perceived risk 0.95, and for UTAUT 0.96. At the same time, top management support had the highest Cronbach's alpha, 0.97, among the five variables.

Design and Procedure

This study employed a quantitative, non-experimental, descriptive-correlational research design to examine the determinants of behavioral intention to use Artificial Intelligence (AI) among decision-makers of multipurpose cooperatives in Region XI. The study utilized Partial Least Squares Structural Equation Modeling (PLS-SEM) to evaluate the hypothesized relationships among the latent constructs. PLS-SEM was selected because the study aimed to explain and predict behavioral intention using multiple latent constructs measured by several observed indicators. Furthermore, PLS-SEM is well-suited to complex predictive models and enables simultaneous assessment of the measurement and structural models.

The quantitative non-experimental technique, according to Curtis, Comiskey, and Dempsey (2016), was used to develop and apply mathematical models, theories, and hypotheses to phenomena. This design examines the current situation and identifies characteristics of a particular phenomenon through observation and the correlation of two or more variables. Lastly, it outlines the prevalence association between factors and predicted events based on available information. Second, Henseler (2012) noted PLS-SEM enables the simultaneous estimation of the measurement model and the structural model. It is particularly appropriate for prediction-oriented studies involving multiple latent variables and complex structural relationships (Henseler, 2012; Hair et al., 2017).

Various statistical tools were used to analyze the data and assess hypotheses at the alpha = 0.05 significance level. The levels of UM, PC, PR, TMS, and BI were determined using the Mean. The Pearson r was then utilized to determine the relationship between the exogenous and endogenous variables. On the other hand, Multiple regression was used to identify the significant predictors of entrepreneurial intentions. Finally, Structural Equation Modeling was used to construct the optimal model of behavioral intentions among Region XI multipurpose cooperatives.

The hypothesized relationships among the latent variables were further evaluated using Partial Least Squares Structural Equation Modeling (PLS-SEM) through SmartPLS. PLS-SEM was selected because it is prediction-oriented and is appropriate for estimating complex models involving multiple latent variables measured by several observed indicators (Hair et al., 2022). The evaluation of the PLS-SEM model consisted of two stages: measurement model assessment and structural model assessment.

The measurement model was assessed by examining indicator reliability, internal consistency reliability, convergent validity, and discriminant validity. Indicator reliability was evaluated using standardized outer loadings, with values of 0.708 or higher considered acceptable. Indicators with loadings between 0.40 and 0.70 were retained only when they contributed to satisfactory construct reliability and validity. Internal consistency reliability was assessed using Cronbach's alpha and Composite Reliability (CR), where values of 0.70 or higher indicated acceptable reliability. Convergent validity was evaluated through the Average Variance Extracted (AVE), with values of 0.50 or higher indicating that the latent construct explained at least 50% of the variance of its indicators. Discriminant validity was established using the Fornell–Larcker criterion and the Heterotrait–Monotrait Ratio (HTMT), with HTMT values below 0.90 indicating adequate discriminant validity (Hair et al., 2022).

The structural model was evaluated after establishing the adequacy of the measurement model. Collinearity among the predictor constructs was examined using the Variance Inflation Factor (VIF), with values below 3.0 indicating the absence of problematic multicollinearity. The significance of the hypothesized relationships was assessed using the bootstrapping procedure with 5,000 resamples, generating standardized path coefficients (β), t-values, p-values, and 95% confidence intervals. The explanatory power of the structural model was assessed using the coefficient of determination (R^2), where values of approximately 0.75, 0.50, and 0.25 represent substantial, moderate, and weak explanatory power, respectively. The contribution of each exogenous construct to the endogenous construct was evaluated using the effect size (f^2), where values of 0.02, 0.15, and 0.35 indicate small, medium, and large effects, respectively. Finally, the model's predictive relevance was assessed using the Stone–Geisser predictive relevance statistic (Q^2) obtained through the blindfolding procedure, with Q^2 values greater than zero indicating that the model possesses predictive relevance (Hair et al., 2022).

The research placed significant emphasis on ethical considerations. Prior to distributing the questionnaire, the survey's initial stages were submitted to the institution’s Ethics Review Committee for evaluation to ensure adherence to ethical guidelines throughout the research process. The proceedings were in accordance with the standards and all necessary requirements were fulfilled. As a result, the researcher obtained an ethics certificate (UMERC-2026 142), affirming the study's ethical compliance.

3. RESULT AND DISCUSSION

The study's findings regarding the research objectives are presented in this part of the paper to provide a clearer understanding of the idea and its implications.

Unified Theory of Acceptance and Use of Technology

The respondents’ assessments of UTAUT model level among multipurpose cooperatives in Region XI. Cooperatives’ UTAUT model obtained an overall mean of 4.139 and a standard deviation of 0.818, described as high. This result indicates that the UTAUT model among cooperative officers, managers, members, decision-makers, and representatives is frequently manifested. All four indicators of the UTAUT model were also rated high.

Table 1
Level of UTAUT Model

Indicators	Standard Deviation	Mean	Description
Performance Expectancy	0.868	4.148	High
Effort Expectancy	0.810	4.165	High
Facilitating Condition	0.840	4.082	High
Social Influence	0.926	4.167	High
Overall	**0.818**	**4.139**	**High**

The result shows that social influence obtained the highest mean among the indicators, and facilitating conditions was the lowest. The results aligned with the study of Venkatesh et al. (2020), who emphasized that social influence significantly affects individuals' intention to use technology, particularly when leaders and peers encourage innovation. This is reflected in the respondents' perception that AI adoption is socially supported, easy to use, beneficial, and backed by adequate organizational resources, indicating strong readiness for implementation in multipurpose cooperatives. In addition, the findings aligned with the Technology Acceptance Model (Davis, 1989) and Dwivedi et al. (2021), which highlight that perceived ease of use and usefulness are key drivers of technology adoption. Likewise, facilitating conditions support adoption, consistent with Venkatesh et al. (2020) and Bag et al. (2021), who stressed the importance of infrastructure and organizational support.

Personal Concern

The respondents' assessments of personal concern in terms of the following indicators: personal development concern and personal wellbeing concern are presented in Table 2. The result shows an overall mean of 4.187, with a standard deviation of 0.861, indicating that that personal concern are perceived as high.

Table 2
Level of Personal Concern

Indicators	Standard Deviation	Mean	Description
Personal Development Concern	0.870	4.213	Very High
Personal Wellbeing Concern	0.919	4.164	High
Overall	**0.861**	**4.187**	**High**

The findings showed that personal development concern was the highest mean among the indicators, and personal wellbeing concern was the lowest. The results aligned with the study of Raisch and Krakowski (2021), who emphasized that perceptions of personal growth, autonomy, and skill relevance significantly shape openness toward AI adoption, as AI introduces both opportunities for development and concerns about changing work roles. It is also consistent with Tarafdar et al. (2020), who noted that technological change can affect employees' psychological well-being, stress, and adaptation, making personal concerns central in technology acceptance. Furthermore, the findings aligned with Human Capital Theory, which posits that individuals are more likely to support innovations that enhance their skills, competencies, and long-term professional value, suggesting that AI is viewed as a tool for both efficiency and capability development in cooperatives. Hence, the result is further supported by Dwivedi et al. (2021) and Venkatesh et al. (2020), who highlighted that AI adoption is more readily accepted when individuals perceive clear benefits for both organizational performance and personal advancement.

Perceived Risk

The respondents' assessments of perceived risk in terms of the following indicators: financial risk, security risk, performance risk, social risk, and psychological risk are presented in Table 3. The result shows an overall mean of 3.574, with a standard deviation of 0.913, indicating that that perceived risk are perceived as high.

Table 3 Level of Perceived Risk

Indicators	Standard Deviation	Mean	Description
Financial Risk	1.056	3.582	High
Security Risk	0.941	3.621	High
Performance Risk	0.971	3.585	High
Social Risk	0.962	3.512	High
Psychological Risk	1.002	3.563	High
Overall	**0.913**	**3.574**	**High**

The findings showed that security risk were the highest means among the indicators, and social risk was the lowest, but all of them are at a high level. This finding is supported by the study of Featherman and Pavlou, who explained that perceived risk is a multidimensional construct that significantly affects users' acceptance and continued use of technology. According to the authors, security, financial, performance, psychological, and social risks influence users' trust and confidence toward technological systems (Featherman & Pavlou, 2003). The high level of security risk found in the present study suggests that users remain cautious about the protection of personal and transactional information.

Furthermore, Sharma et al. (2022) highlighted that social risk remains an important consideration in technology adoption because users may worry about how others perceive their use of certain systems or platforms. The study explained that social influence and fear of negative judgment can affect confidence and adoption behavior (Sharma et al., 2022).

Top Management Support

The respondents' assessments of top management support in terms of the following indicators: provide resources, structural arrangements, communication, expertise and power are presented in Table 4. The result shows an overall mean of 4.094, with a standard deviation of 0.805, indicating that that top management support are perceived as high.

Table 4 Level of Top Management Support

Indicators	Standard Deviation	Mean	Description
Provide Resources	0.856	4.104	High

Structural Arrangements	0.861	4.091	High
Communication	0.930	4.100	High
Expertise	0.961	4.115	High
Power	0.856	4.070	High
Overall	**0.805**	**4.094**	**High**

The findings showed that expertise was the highest mean among the indicators, and power was the lowest. This finding is supported by Al-Emran et al. (2020), who emphasized that top management support is a key factor in successful technology adoption, as leadership commitment through expertise, communication, and resource provision strengthens employee confidence and acceptance. Similarly, Aboelmaged (2021) explained that strong managerial support enhances innovation adoption by providing strategic direction, funding, and coordination needed for implementation. This is further reinforced by Dubey et al. (2022), who noted that effective communication and proper structural arrangements from top management improve employee engagement and reduce resistance to change. In addition, Sharma and Singh (2023) highlighted that leadership influence and managerial authority are crucial in sustaining commitment to digital transformation.

Behavioral Intention

The respondents' assessments of behavioral intention in terms of the following indicators: actual use and future use are presented in Table 5. The result shows an overall mean of 4.098, with a standard deviation of 0.897, indicating that that behavioral intention are perceived as high. This indicates that respondents demonstrate a strong willingness and readiness to use the system consistently.

Table 5
Level of Behavioral Intention

Indicators	Standard Deviation	Mean	Description
Actual Use	1.053	4.099	High
Future Use	0.975	4.096	High
Overall	**0.897**	**4.098**	**High**

The findings showed that actual use was the highest mean among the indicators, and future use was the lowest. This implies that users not only currently engage with the artificial intelligence but also intend to continue using it in the future, reflecting sustained acceptance and positive user experience. Still, the result is strongly supported by the Unified Theory of Acceptance and Use of Technology (UTAUT) of Venkatesh et al. (2012), which states that behavioral intention is the strongest predictor of actual use, especially when users perceive high performance expectancy and facilitating conditions. This is also consistent with Dwivedi et al. (2020), who found that behavioral intention consistently drives actual usage across various digital technologies. Likewise, Tamilmani et al. (2021) emphasized that perceived usefulness, habit, and satisfaction strengthen continued use, while Sharma et al. (2022) highlighted that strong behavioral intention reflects user trust and perceived value, leading to sustained engagement. Overall, the high behavioral intention in this study indicates strong acceptance, satisfaction, and continued future use of the artificial intelligence.

Relationship Among UTAUT Model, Personal Concern, Perceived Risk, Top Management Support, and Behavioral Intention

The significance of the relationship between the UTAUT model and behavioral intentions among multipurpose cooperatives in Region XI is shown in Table 6, with a combined computed r value of 0.837 and a p-value less than 0.05, indicating significance. The study found a significant relationship between the exogenous variables and the behavioral intention to use Artificial Intelligence (AI) among decision-makers of multipurpose cooperatives in Region XI.

Specifically, the Unified Theory of Acceptance and Use of Technology (UTAUT) model demonstrated the strongest relationship with behavioral intention, yielding a correlation coefficient (r) of 0.837 with a p-value < 0.05. This result led to the rejection of the null hypothesis, confirming that UTAUT is significantly related to behavioral intention.

Table 6
Correlation Matrix of UTAUT Model, Personal Concern, Perceived Risk, Top Management Support, and Behavioral Intention

Paired Variables	r-value	p-value	Decision
UTAUT Model – Behavioral Intention	0.837	p < .001	Reject Ho
Personal Concern – Behavioral Intention	0.797	p < .001	Reject Ho
Perceived Risk – Behavioral Intention	0.745	p < .001	Reject Ho
Top Management Support – Behavioral Intention	0.459	p < .001	Reject Ho

The findings imply that as respondents' perceptions regarding performance expectancy, effort expectancy, facilitating conditions, and social influence increase, their intention to use AI also increases. This result strongly supports the theory of Venkatesh et al. (2020), which emphasized that individuals are more likely to adopt technology when they perceive it as beneficial, easy to use, socially encouraged, and supported by adequate organizational infrastructure.

The strong relationship between UTAUT and behavioral intention is consistent with previous studies on AI and technology adoption. Dwivedi et al. (2021) found that UTAUT variables remain among the strongest predictors of AI adoption in organizational settings because users tend to embrace technologies that improve productivity and organizational performance. Similarly, Fred Davis (1989) explained through the Technology Acceptance Model (TAM) that perceived usefulness and perceived ease of use significantly shape users' behavioral intentions toward technology adoption. The present study extends these findings within the context of multipurpose cooperatives, suggesting that cooperative leaders are more inclined to use AI when they perceive it as efficient, manageable, and organizationally supported.

Influence of UTAUT Model, Personal Concern, Perceived Risk and Top Management Support for the Behavioral Intention

The regression analysis of the variables is presented in Table 7. Changes in the UM, PC, PR, and TMS are associated with changes in BI, as shown by the regression analysis. The result revealed that the model integrating the UTAUT model, personal concern, perceived risk, and top management support can account for approximately 71.4% of the variance in behavioral intention. The UTAUT model increases behavioral intention by 0.6491 for every unit increase in the variable, assuming that the other variables remain constant. Similarly, personal concern increases behavioral intention by 0.1522 for each additional unit when the other variables remain unchanged. Similarly, top management support increases behavioral intention by 0.139 for each unit increase, while holding the other variables constant.

Table 7
Influence of UTAUT Model, Personal Concern, Perceived Risk and Top Management Support on Behavioral Intention

Behavioral Intention									
Exogenous Variables	***B***	**β**	***t***	***Sig.***	**R**	**R2**	ΔR	**F**	ρ
Constant	.1347		1.036	.300	.845	.714	.711	260.850	.000
UTAUT Model	.6491	.591	8.662	.000					
Personal Concern	.1522	.146	2.107	.036					
Perceived Risk	.0193	.020	.608	.543					
Top Management Support	.1393	.125	2.410	.016					

Among the predictors, the UTAUT model emerged as the strongest predictor of behavioral intention, as reflected by its beta coefficient of 0.591 and significant t-value of 8.662 (p-value < 0.05). This indicates that respondents' behavioral intention is strongly influenced by the factors embedded in the UTAUT model, such as performance expectancy, effort expectancy, social influence, and facilitating conditions. Likewise, personal concern significantly influences behavioral intention, as evidenced by its t-value of 2.107 (p-value < 0.05). The result implies that respondents' personal awareness, attitudes, and concerns toward the system positively affect their intention to use it. Furthermore, top management support also significantly influences behavioral intention, having a t-value of 2.410 (p-value < 0.05). This finding suggests that organizational support, leadership encouragement, provision of resources, and managerial involvement strengthen users' willingness to adopt and continuously use the artificial intelligence.
However, perceived risk is unlikely to have any bearing on behavioral intention. This result is evident from its t-value of 0.608 with a p-value greater than 0.05, indicating that the variable does not significantly influence behavioral intention. Although respondents may recognize certain risks associated with the system, such risks do not substantially affect their intention to use the technology. This suggests that the positive influences of the UTAUT model, personal concerns, and organizational support outweigh the negative perceptions associated with risk.

Table 8
Structural Path Coefficients

Exogenous Variables	**Path**	**Standardized Coefficient β**	**Sig.**	**Interpretation**
UTAUT Model	UM → BI	0.6491	0.000	Significant predictor
Personal Concern	PC → BI	0.1522	0.036	Significant predictor
Perceived Risk	PR → BI	0.0193	0.543	Not significant
Top Management Support	TMS → BI	0.1393	0.016	Significant predictor

The findings further revealed that UTAUT Model had a significantly positive contribution to behavioral intention (β = 0.6491, p = 0.000). This indicates that respondents' behavioral intention is strongly influenced by the factors embedded in the UTAUT model, such as performance expectancy, effort expectancy, social influence, and facilitating conditions. Meanwhile, the analysis showed perceived risk is unlikely to have any bearing on behavioral intention. Although respondents may recognize certain risks associated with the system, such risks do not substantially affect their intention to use the technology. This suggests that the positive influences of the UTAUT model, personal concerns, and organizational support outweigh the negative perceptions associated with risk.

PLS-SEM Structural Model

Following confirmation of the measurement model's reliability and validity, the structural model was evaluated to assess the relationships among the latent constructs. In accordance with the recommendations of Hair et al. (2022), the assessment included examining collinearity among predictor constructs, evaluating structural path coefficients via bootstrapping, and testing hypotheses, including the coefficient of determination (R^2), effect size (f^2), and predictive relevance (Q^2).

Prior to evaluating the structural relationships, collinearity among the predictor constructs was assessed using the Variance Inflation Factor (VIF). The results indicated that the predictor constructs exhibited acceptable levels of collinearity for structural model estimation. Table 9 presents the structural path coefficients.

Table 9
Structural Path Coefficients

Path	H	β	SE	t	p	Decision	Direction
UTAUT Model → Behavioral Intention	H1	0.5913	0.0683	8.6622	0	Supported	Positive
Personal Concern → Behavioral Intention	H2	0.1459	0.0692	2.1074	0.0357	Supported	Positive
Perceived Risk → Behavioral Intention	H3	0.0196	0.0323	0.6083	0.5433	Not Supported	Negligible
Top Mgmt Support → Behavioral Intention	H4	0.1249	0.0518	2.4101	0.0164	Supported	Positive

The results revealed that the UTAUT Model had a positive and statistically significant influence on Behavioral Intention (β = 0.591, t = 8.662, p < .001). This indicates that respondents who perceived artificial intelligence as useful, easy to use, socially supported, and facilitated by organizational resources were more likely to have a stronger intention to adopt it in their cooperatives. Thus, Hypothesis 1 was supported.

Similarly, Personal Concern exerted a positive and statistically significant effect on Behavioral Intention (β = 0.146, t = 2.107, p = .036). This finding suggests that respondents' personal concerns regarding the use of artificial intelligence significantly influenced their intention to adopt the technology. Accordingly, Hypothesis 2 was supported.

In contrast, Perceived Risk did not significantly influence Behavioral Intention (β = 0.020, t = 0.608, p = .543). The relationship failed to reach statistical significance, indicating that perceived risks associated with artificial intelligence did not substantially affect the respondents' intention to use the technology after considering the effects of the other predictor variables. Therefore, Hypothesis 3 was not supported.

Finally, Top Management Support demonstrated a positive and statistically significant relationship with Behavioral Intention (β = 0.125, *t* = 2.410, *p* = .016). This finding implies that organizational commitment and support from top management enhance the willingness of decision-makers to adopt artificial intelligence. Hence, Hypothesis 4 was supported.

Overall, the structural model supported three of the four proposed hypotheses. Among the predictor variables, the UTAUT Model emerged as the strongest determinant of Behavioral Intention, as evidenced by its highest standardized path coefficient. In comparison, Personal Concern and Top Management Support exhibited weaker but statistically significant positive effects, whereas Perceived Risk did not significantly contribute to predicting Behavioral Intention.

The explanatory and predictive capability of the proposed structural model was evaluated using the coefficient of determination (R^2), adjusted coefficient of determination (Adjusted R^2), F-statistic, effect size (f^2), and predictive relevance (Q^2). The results are presented in Table 10.

Table 10
Model Fit and Predictive Relevance

Criterion	Value	Threshold	Interpretation
R^2 (Behavioral Intention)	0.7135 (71.35%)	> 0.10	High explanatory power
Adjusted R^2	0.7108	> 0.10	Acceptable
F-statistic	260.85 (df=4, 419)	p < .001	Model is significant
f^2 (UTAUT → BI)	0.49	> 0.35 = large	Large effect
f^2 (Personal Concern → BI)	0.03	0.02–0.15 = small	Small effect
f^2 (Perceived Risk → BI)	< 0.01	< 0.02 = negligible	Negligible effect
f^2 (Top Mgmt Support → BI)	0.04	0.02–0.15 = small	Small effect
Q^2 (predictive relevance)	0.714	> 0	Model has predictive relevance

The coefficient of determination (R^2) for Behavioral Intention was 0.7135, indicating that approximately 71.35% of the variance in behavioral intention was jointly explained by the UTAUT Model, Personal Concern, Perceived Risk, and Top Management Support. According to Hair et al. (2022), this level of explained variance indicates High explanatory power, suggesting that the proposed model adequately explains the behavioral intention to adopt artificial intelligence among decision-makers of multipurpose cooperatives. Similarly, the Adjusted R^2 value of 0.7108 indicates that the model retains a high level of explanatory capability even after adjusting for the number of predictor variables, demonstrating the robustness of the proposed structural model.

The overall significance of the structural model was further confirmed by the F-statistic of 260.85 (df = 4, 419, p < .001), indicating that the predictor constructs collectively provide a statistically significant explanation of Behavioral Intention. This finding supports the adequacy of the proposed structural model in explaining the endogenous construct.

The contribution of each predictor variable was assessed using effect size (f^2). The results indicate that the UTAUT Model exerted a large effect on Behavioral Intention ($f^2 = 0.49$), making it the strongest predictor among the exogenous constructs. In contrast, Personal Concern ($f^2 = 0.03$) and Top Management Support ($f^2 = 0.04$) demonstrated small effect sizes, indicating that they contributed positively but to a lesser extent. Meanwhile, Perceived Risk ($f^2 < 0.01$) exhibited a negligible effect, suggesting that its contribution to the explained variance of Behavioral Intention was minimal.

Finally, the model's predictive capability was evaluated using the Stone–Geisser predictive relevance (Q^2) statistic. The obtained Q^2 value of 0.714 exceeded the recommended threshold of zero, indicating that the structural model possesses adequate predictive relevance. This finding suggests that the proposed model has satisfactory capability in predicting Behavioral Intention beyond merely explaining the observed data.

Overall, the structural model demonstrated satisfactory explanatory power, statistical significance, and predictive relevance. The findings further indicate that the UTAUT Model serves as the principal determinant of Behavioral Intention, while Personal Concern and Top Management Support provide smaller yet meaningful contributions. Conversely, Perceived Risk contributed minimally to explaining respondents' behavioral intention to adopt artificial intelligence.

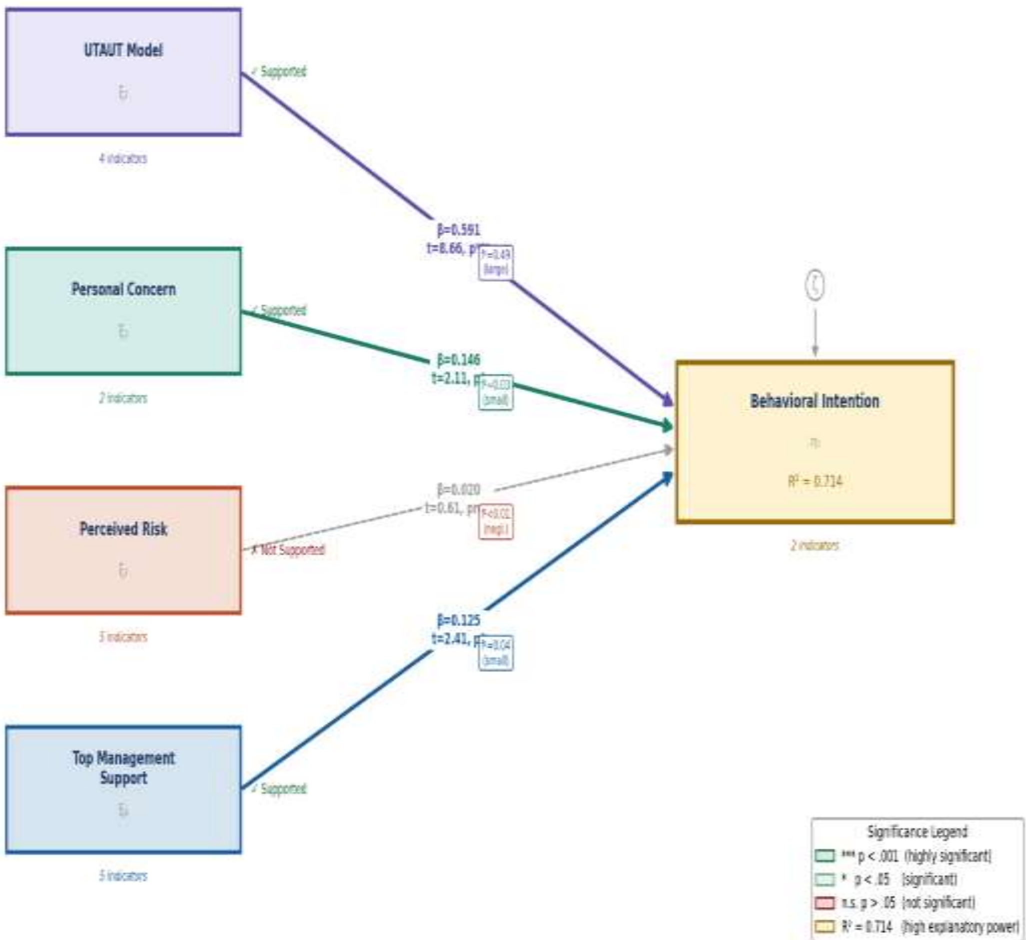

Figure 2. Final PLS-SEM Structural Model on Behavioral Intention

Figure 2 presents the final structural model of the proposed PLS-SEM analysis. The model illustrates the statistically significant relationships among the latent constructs based on the bootstrapping results. The standardized path coefficients indicate that the UTAUT Model exerted the strongest positive influence on Behavioral Intention ($\beta = 0.591$), followed by Personal Concern ($\beta = 0.146$) and Top Management Support ($\beta = 0.125$). In contrast, Perceived Risk did not demonstrate a statistically significant effect on Behavioral Intention ($\beta = 0.020$, $p > .05$). The model further showed substantial explanatory power ($R^2 = 0.7135$) and adequate predictive relevance ($Q^2 = 0.714$), supporting the proposed structural model.
Overall, the final structural model supports three of the four hypothesized relationships, indicating that behavioral intention to adopt artificial intelligence among decision-makers of multipurpose cooperatives is primarily influenced by the UTAUT Model, with additional contributions from Personal Concern and Top Management Support. Perceived Risk, however, did not significantly influence behavioral intention in the presence of the other predictor constructs.

4. CONCLUSION AND RECOMMENDATION

The study concludes that the levels of the UTAUT Model, Personal Concern, Top Management Support, and Behavioral Intention were all high among officers, managers, members, decision-makers, and representatives of multipurpose cooperatives in Region XI. The findings further revealed that significant relationships exist between all exogenous variables and Behavioral Intention. However, only the UTAUT Model, Personal Concern, and Top Management Support significantly influenced Behavioral Intention, while Perceived Risk did not have a significant effect. Among the predictors, the UTAUT Model emerged as the strongest determinant of Behavioral Intention toward AI adoption.
Moreover, the structural model explained 71.35% of the variance in Behavioral Intention, indicating a strong and robust predictive model. These findings confirm that AI adoption among multipurpose cooperatives is primarily driven by perceptions of usefulness, ease of use, social influence, facilitating conditions, organizational support, and personal development considerations. Thus, strengthening these factors can significantly enhance the willingness of cooperative decision-makers to adopt and utilize AI technologies in their organizational operations.
The findings of the study support the Unified Theory of Acceptance and Use of Technology (UTAUT) developed by Venkatesh et. al., (2003). The theory emphasizes that performance expectancy, effort expectancy, social influence, and facilitating conditions are critical determinants of behavioral intention toward technology adoption.
Based on the findings, it is recommended that multipurpose cooperatives strengthen facilitating conditions by investing in technological infrastructure, AI tools, technical support systems, and continuous employee training programs to improve AI readiness and adoption. Organizations should likewise implement professional development and well-being initiatives that address employees' concerns regarding technological adaptation, anxiety, and work-life balance. Furthermore, top management should enhance leadership involvement through effective communication, strategic resource allocation, and active support for AI-related initiatives to foster a culture of innovation and technology acceptance.
In addition, government agencies and cooperative organizations should collaborate in promoting AI readiness through capacity-building programs, technical assistance, and supportive policies that encourage digital transformation. Future researchers are also encouraged to examine additional variables such as trust, organizational readiness, innovation culture, digital competence, technology anxiety, and

perceived value to further improve the explanatory power of the model and expand the understanding of AI adoption in various organizational contexts.

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