Technology Adoption and Usage Behaviors in Field Incident Management System Utilization

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***Abstract*—This study utilized the Unified Theory of Acceptance and Use of Technology (UTAUT) model to analyze the adoption and utilization of field incident management system (IMS) in a manufacturing organization. The study specifically focused on the role of behavior as a key factor in the adoption and utilization of incident management system. Data was collected through a survey of employees who had utilized the IMS system and the UTAUT model was used to analyze the data. The results indicated that behavior in the system significantly influenced the adoption and utilization of IMS. The study also found that the UTAUT model provided a useful framework for understanding the adoption and utilization of IMS, particularly the importance of performance expectancy, effort expectancy, social influence, and facilitating conditions. The study provides valuable insights for organizations looking to implement IMS and improve their incident management processes. It highlights the importance of building behavior in the system through appropriate user experience and user training. The findings of this study have important implications for manufacturing organizations seeking to enhance their incident management procedures through the adoption and utilization of IMS.**

Keywords—UTAUT; field incident management system (FIMS); regression analysis; user intention and acceptance; system adoption; usage behavior; manufacturing; IMS; effort expectancy; performance expectancy; social influence; facilitating conditions; behavioral intention; ANOVA

I. Introduction

Effective incident management is critical to the success of organizations in today's complex and fast-paced business environment. Incident management systems (IMS) have become essential tools for managing incidents and minimizing their impact on business operations. Among the various IMS options available, Field IMS has gained popularity [1]. However, the adoption and deployment of IMS in organizations can be challenging [1, 7, 13]. To understand the factors influencing IMS adoption and use, the Unified Theory of Acceptance and Use of Technology (UTAUT) paradigm has been widely used [1, 16]. This paradigm identifies four key drivers of technological acceptability and utilization: performance expectations, effort expectations, societal impact, and facilitating conditions [2, 3, 5, 12]. In recent years, behavior has been recognized as a significant factor in technology acceptance and use in business settings [3, 14, 17, 19].

This study focuses on the role of behavior in the adoption and utilization of Field IMS within organizations, using the UTAUT paradigm. The objective of the study is to provide recommendations for organizations seeking to enhance their incident management practices and gain insights into the factors that influence IMS adoption and use. The review of literature highlights the importance of IMS and the UTAUT paradigm in the context of technology adoption and use within organizations. The research question and hypotheses are introduced, followed by a description of the study's methodologies, including data collection processes. The study's findings are presented, followed by a discussion of their implications. Finally, conclusions and suggestions for future research are provided.

This study significantly contributes to the existing knowledge on technology adoption and deployment in businesses. The findings have practical implications for firms aiming to implement Field IMS and improve their incident management procedures. The study emphasizes the role of behavior in the adoption and utilization of Field IMS and demonstrates the applicability of the UTAUT model in understanding this process.

The paper identifies and examines the factors that influence the adoption and utilization of Field IMS, providing valuable insights for researchers and managers. Its specific focus on field incident management sets it apart from other studies, addressing a specific need and offering insights that may not be applicable to broader technology adoption contexts. This contextualization highlights the necessity of the paper, filling a gap in the literature by exploring technology adoption within a specific industry or setting. Also, the paper sheds light on the relative importance of different components within the UTAUT Model, with facilitating conditions and user effort emerging as the most influential factors in Field IMS adoption and utilization. This finding underscores the significance of organizational support, resources, infrastructure, ease of use, user-friendly interfaces, and training programs in promoting technology adoption and usage behaviors.

The paper acknowledges the study's limitations, including the sample size and reliance on self-reported data, and suggests directions for future research. It calls for larger and more diverse samples to enhance the robustness and generalizability of the findings. Incorporating objective measures or observational data is recommended to improve the validity of results.

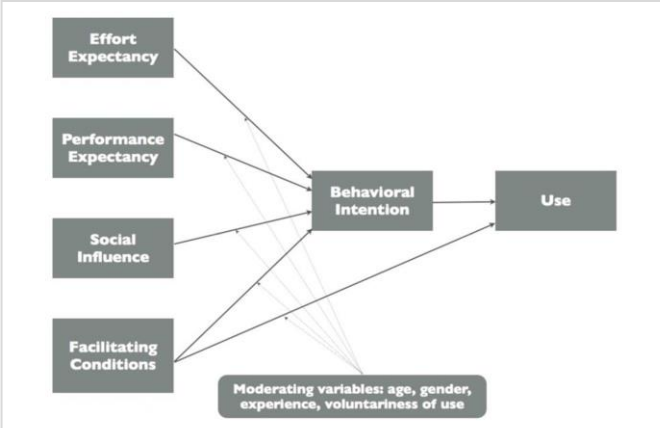

Fig. 1. The UTAUT model based on the original framework by [16].

The paper proposes exploring additional variables to enhance the predictive power of the UTAUT Model, such as perceived risk, trust, or personal innovativeness. This forward-thinking approach demonstrates the paper's commitment to advancing the understanding of technology adoption by incorporating relevant factors.

The value lies in its contextual focus, contribution to the theoretical understanding of technology adoption and usage behaviors, and identification of influential factors specific to field incident management. It also highlights the need for further research to enhance the model's performance and validate the findings in different contexts, ultimately improving the understanding of technology adoption and usage behaviors. The practical implications of the study's findings can inform decision-making, resource allocation, and technology acceptance and usage within organizations, leading to increased productivity, efficiency, and overall performance.

II. Related Works

This review aimed to explore the factors affecting the adoption of Field Incident Management System (IMS) using the Unified Theory of Acceptance and Use (UTAUT) model as illustrated in Fig. 1. The UTAUT model is used to understand factors influencing the acceptance and use of information technology (IT) systems [3]. The findings of the literature review revealed that several factors influence the adoption and use of Field IMS [4].

According to the UTAUT model, performance expectancy, effort expectancy, social influence and facilitating conditions significantly impact the decision to adopt new information technology systems such as Field Incident Management System [5].

Performance expectancy refers to the degree to which a user believes that using an information technology system will improve their job performance. Some of the factors that contribute to performance expectancy include the system's perceived usefulness, ease of use, and compatibility with existing processes [6]. Effort expectancy, on the other hand, refers to the degree of ease associated with using an IT system [7, 8]. This encompasses factors such as the system's complexity, technical support available, and the user's perceived level of skill required to use it. Social influence, as a factor in the UTAUT model, refers to how social factors such as colleagues and management can encourage or discourage users from adopting new IT systems such as Field IMS [8, 9].

Social influence can also include the opinions of external stakeholders and experts. Facilitating conditions are another important factor in the UTAUT model, which include both technical and organizational support aspects such as training, infrastructure availability, and resource availability, which can impact users' ability to adopt and utilize new IT systems [9]. Taken together, the findings from this literature review underscore the multifaceted nature of factors that influence adoption and use of new IT systems within organizations.

A. Attitude, Behavior, And Usage of a Field Incident Management System

1) Behavior and Intention to use FIMS: Behavior is an essential factor in the adoption and usage of technology. The authors in [10] found that behavior has a positive effect on the intention to use Internet of Things (IoT) devices in e-Health. The study applied a modified UTAUT model to investigate the role of behavior in the adoption of IoT in a consumer context. The findings revealed that behavior positively affects the behavioral intention to use IoT devices, which is consistent with previous studies [10]. Therefore, behavior can be considered a critical factor in the adoption and usage of FIMS. Factors Influencing Healthcare Professionals to Adopt AIMDSS [11] conducted a study to investigate the factors that impact healthcare professionals' adoption of artificial intelligence-based medical diagnosis support systems (AIMDSS) using the UTAUT framework. The results showed that performance expectancy, effort expectancy, and social influence positively influenced the intention to use AIMDSS [11]. However, facilitating conditions did not show a significant effect on the intention to use. These findings suggest that perceived usefulness and ease of use are significant determinants of intention to use technology [12].

B. Behavior Theory in Field Incident Management System

1) Behavior and FIMS acceptance: Behavior has been identified as a significant factor in the adoption of technology, including FIMS [16]. According to [13], behavior has a direct and positive impact on the acceptance of mobile medical platforms. Similarly, [10] found that behavior significantly influences the intention to use the Internet of Things (IoT) in e-Health. The study showed that behavior had a more significant effect on the intention to use the IoT than performance expectancy, effort expectancy, and social influence. In the context of FIMS, [14] found that behavior significantly influenced behavioral intention to use mobile health (mHealth) applications. The study found that behavior moderated the relationship between performance expectancy and behavioral intention. Similarly, [15] identified behavior as a significant factor in the acceptance of telemedicine in the Philippines. The study found that behavior had a positive effect on perceived usefulness and perceived ease of use.

2) UTAUT and Behavior: Several studies have investigated the relationship between behavior and the constructs of the UTAUT model [17]. For example, [11] found that performance expectancy, effort expectancy, and social influence were significant predictors of the adoption of artificial intelligence-based medical diagnosis support systems. The study also found that behavior moderated the relationship between performance expectancy and intention to use the system. Study [17] investigated the factors that influence consumer behavior in Internet of Things (IoT) products and applications. The study identified performance expectancy, effort expectancy, and social influence as significant predictors of consumer behavior in IoT. Similarly, [20] integrated the UTAUT model and the Task-Technology Fit (TTF) model to understand the acceptance of healthcare wearable devices. The study found that behavior moderated the relationship between performance expectancy and behavioral intention. The adoption of FIMS is significantly influenced by user acceptance. Behavior has been identified as a significant factor in the acceptance of FIMS, and it has a direct and positive impact on behavioral intention to use the system [18].

The UTAUT model has been a popular framework for studying user acceptance of technology. Several studies have investigated the relationship between behavior and the constructs of the UTAUT model, with behavior moderating the relationship between performance expectancy and behavioral intention [18, 19]. Therefore, behavior should be considered an essential factor when designing and implementing FIMS in various fields [19].

C. UTAUT in Field Incident Management System

1) Behavior and User Intention: Research [10] found that behavior plays a significant role in the intention to use the Internet of Things (IoT) in e-Health. Similarly, [20] investigated the consumer acceptance of healthcare wearable devices and found that behavior is a vital determinant of user acceptance. The study [11] investigated the factors impacting the adoption of artificial intelligence-based medical diagnosis support systems (AIMDSS) and found that behavior, compatibility, and perceived usefulness are the most significant determinants of user adoption.

The literature reviewed in this study indicates that the UTAUT framework is an effective model for analyzing technology acceptance in the context of FIMS adoption. The studies identified several factors influencing the adoption of technology, including behavior, user intention, and acceptance. The findings of this literature review can be used to inform the design of FIMS systems and to develop strategies to increase user acceptance and adoption. The UTAUT framework can also be applied to other technologies not limited to manufacturing but also to other industries that has an incident management to gain a deeper understanding of the factors influencing technology adoption [20].

III. METHODOLOGY

The aim of this study is to investigate the factors that influence behavior and its impact on the intention to adopt IMS. To achieve this, the study will use the UTAUT theoretical framework, which has been widely used to examine technology adoption in organizations [21]. Specifically, the study will focus on the relationships between the four main constructs of UTAUT, i.e., performance expectancy, effort expectancy, social influence, and facilitating conditions, and their relationships with behavior intention and use behavior, and how they affect behavioral intention and use behavior [22, 23, 24, 25, 26]. To collect data, a quantitative research method will be used, and a survey questionnaire will be designed based on the UTAUT model as shown in Fig. 2. The questionnaire will include items related to the four main constructs of UTAUT and behavior, which will be measured using a 5-point Likert scale. The survey will be distributed to employees who use IMS in their daily work.

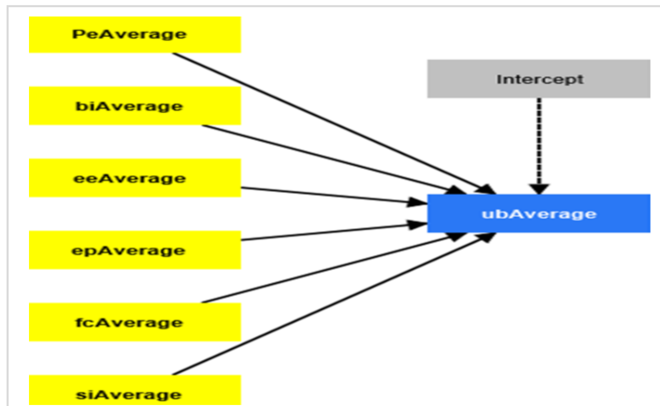

Fig. 2. Adapted model of UTAUT by [16].

To analyze the data, regression analysis will be used. Regression analysis is a statistical method that examines the relationship between variables and allows the researcher to identify the variables that have a significant effect on the outcome variable [27]. Regression analysis will enable the identification of the variables that significantly affect the intention to adopt and use IMS [28, 29]. It will be a use of a convenience sampling method to gather data from employees who use IMS in their daily work [30, 31, 32, 33]. A power analysis will be conducted to determine the appropriate sample size. Organizations that have implemented IMS will be surveyed, and the study will adhere to ethical standards. The results will have practical applications for organizations that are considering the adoption of IMS.

IV. RESULTS

A. Summary Coefficient

The researchers utilized the UTAUT Model to examine the factors influencing the dependent variable. The Smart PLS analysis yielded several interesting findings.

Regarding the predictor variables, it is clearly shown in Table I that siAverage demonstrated a non-significant positive relationship ($\beta = 0.052$, $p = 0.584$) with the dependent variable. This suggests that the social influence factor may have a weak impact on the outcome. Similarly, eeAverage exhibited a non-significant weak positive relationship (β = 0.122, p = 0.210), indicating that the effort expectancy factor may not significantly affect the dependent variable. On the other hand, PeAverage displayed a marginally significant negative relationship (β = -0.186, p = 0.053) with the dependent variable. This implies that the performance expectancy factor may have a weak negative influence on the outcome, although further research is needed to confirm this relationship. Two variables, fcAverage and epAverage, showed significant positive associations with the dependent variable. fcAverage had a moderate positive relationship (β = 0.223, p = 0.021), suggesting that facilitating conditions may play an important role in shaping the outcome. Similarly, epAverage exhibited a moderate positive relationship (β = 0.246, p = 0.013), indicating that effort expended by users may significantly impact the dependent variable. Lastly, biAverage and the intercept term did not significantly affect the dependent variable, as indicated by their non-significant coefficients (p > 0.05).

TABLE I. SUMMARY OF COEFFICIENT

Constructs	Unstandardized coefficients	Standardized coefficients	SE	T value	P value
siAverage	0.045	0.052	0.082	0.550	0.584
PeAverage	-0.166	-0.186	0.085	1.961	0.053
fcAverage	0.174	0.223	0.074	2.344	0.021
epAverage	0.245	0.246	0.097	2.521	0.013
eeAverage	0.102	0.122	0.081	1.262	0.210
biAverage	0.004	0.005	0.085	0.051	0.959
Intercept	2.678	0.000	0.815	3.286	0.001

B. Summary ANOVA

The ANOVA results provide valuable insights into the overall model fit and the significance of the regression. The total sum of squares indicates the total variability in the dependent variable, which was found to be 10.222. The degrees of freedom (df) associated with the total sum of squares are 99.

The error sum of squares represents the unexplained variability in the dependent variable, which amounted to 8.199. The error degrees of freedom are 93. The mean square error, calculated by dividing the error sum of squares by the error degrees of freedom, is 0.088. The regression sum of squares reflects the portion of the total variability in the dependent variable that is explained by the predictor variables in the model. In this case, the regression sum of squares was found to be 2.023. The regression degrees of freedom, which correspond to the number of predictor variables in the model, are 6. The mean square regression, calculated by dividing the regression sum of squares by the regression degrees of freedom, is 0.337.

The F-test statistic is computed by dividing the mean square regression by the mean square error. In the analysis, the F-value was 3.825, indicating a significant relationship between the predictor variables and the dependent variable. The associated p-value of 0.000 further confirms the statistical significance. These results suggest that the predictor variables included in the UTAUT Model collectively explain a significant portion of the variance in the dependent variable. The model demonstrates a good fit, as indicated by the significant F-test and low p-value.

Researchers and practitioners can interpret these findings as evidence supporting the usefulness of the UTAUT Model in understanding the factors influencing the dependent variable. The identified predictor variables contribute significantly to explaining the variation in the outcome, indicating their importance in technology adoption and usage behaviors.

C. Unstandardized and standardized Coefficients

1) The unstandardized and standardized coefficients provide important insights into the magnitude and direction of these relationships. In Table II, the unstandardized coefficients of the study were evidently presented.

siAverage: The unstandardized coefficient for siAverage is 0.045. This suggests that a one-unit increase in siAverage is associated with a 0.045-unit increase in the dependent variable.

PeAverage: The unstandardized coefficient for PeAverage is -0.166. This indicates that a one-unit increase in PeAverage is associated with a decrease of 0.166 units in the dependent variable.

fcAverage: The unstandardized coefficient for fcAverage is 0.174. This means that a one-unit increase in fcAverage is associated with a 0.174-unit increase in the dependent variable.

epAverage: The unstandardized coefficient for epAverage is 0.245. This implies that a one-unit increase in epAverage is associated with a 0.245-unit increase in the dependent variable.

eeAverage: The unstandardized coefficient for eeAverage is 0.102. This suggests that a one-unit increase in eeAverage is associated with a 0.102-unit increase in the dependent variable.

biAverage: The unstandardized coefficient for biAverage is 0.004. This indicates that a one-unit increase in biAverage is associated with a 0.004-unit increase in the dependent variable.

Intercept: The unstandardized coefficient for the intercept term is 2.678. This term represents the constant or baseline value of the dependent variable when all predictor variables are zero.

TABLE II. UNSTANDARDIZED COEFFICIENT

Constructs	ubAverage
siAverage	0.045
PeAverage	-0.166
fcAverage	0.174
epAverage	0.245
eeAverage	0.102
biAverage	0.004
Intercept	2.678

2) Switching to the standardized coefficients as shown in Table III, findings:

siAverage: The standardized coefficient for siAverage is 0.052. This indicates the strength and direction of the relationship between siAverage and the dependent variable, taking into account the scales and variances of both variables.

PeAverage: The standardized coefficient for PeAverage is -0.186. This provides information about the standardized effect of PeAverage on the dependent variable.

fcAverage: The standardized coefficient for fcAverage is 0.223. This quantifies the standardized effect of fcAverage on the dependent variable.

epAverage: The standardized coefficient for epAverage is 0.246. This represents the standardized effect of epAverage on the dependent variable.

eeAverage: The standardized coefficient for eeAverage is 0.122. This signifies the standardized effect of eeAverage on the dependent variable.

biAverage: The standardized coefficient for biAverage is 0.005. This shows the standardized effect of biAverage on the dependent variable.

Intercept: The standardized coefficient for the intercept term is 0.000. Since it is zero, the intercept does not contribute directly to the explanation of the dependent variable.

TABLE III. STANDARDIZED COEFFICIENT

Constructs	ubAverage
siAverage	0.052
PeAverage	-0.186
fcAverage	0.223
epAverage	0.246
eeAverage	0.122
biAverage	0.005
Intercept	0.000

These coefficients provide valuable insights into the relative importance and impact of the predictor variables on the dependent variable within the UTAUT Model. Researchers and practitioners can use these coefficients to understand which variables have stronger or weaker effects and prioritize their focus accordingly.

D. Quality Criteria

The results provide insights into the goodness-of-fit of the model and the presence of multicollinearity. The R-square value, which represents the proportion of variance explained by the model, is 0.198. This indicates that the predictor variables included in the UTAUT Model explain approximately 19.8% of the variance in the dependent variable. The R-square adjusted value, which considers the number of predictor variables and sample size, is 0.146. This adjusted value accounts for the complexity of the model and provides a more conservative estimate of the explained variance.

The Durbin-Watson test statistic is used to assess the presence of autocorrelation in the model residuals. In this case, the test yielded a value of 1.917, which falls within the acceptable range of values (between 0 and 4). This suggests that there is no significant autocorrelation in the model residuals. Moving on to the collinearity statistics, we examined the Variance Inflation Factor (VIF) for each predictor variable. The VIF measures the extent to which multicollinearity may be present in the model. In our analysis, all VIF values are close to 1, indicating a lack of substantial multicollinearity among the predictor variables. This suggests that the predictor variables in the UTAUT Model are relatively independent of each other and do not exhibit high collinearity.

Additionally, we examined the condition index, which provides information about the collinearity structure among the predictor variables. The condition index values, along with their corresponding eigenvalues, indicate the degree of collinearity among the variables. In our analysis, the condition index values range from 1 to 78.594, with higher values indicating stronger collinearity. The eigenvalues associated with the condition indices show that the majority of the variables do not exhibit severe collinearity, except for index 6, where an eigenvalue of 6.966 is observed. This indicates that the variables included in this condition index may have a higher degree of collinearity.

The results of the quality criteria and collinearity statistics suggest that the UTAUT Model provides a moderate level of explanation for the dependent variable, without significant multicollinearity among the predictor variables. However, the presence of some collinearity in condition index 6 should be taken into consideration. Researchers and practitioners can interpret these findings as an indication that the UTAUT Model, while explaining a modest proportion of the variance in the dependent variable, may still provide meaningful insights into the factors influencing technology adoption and usage behaviors. Future research should explore additional variables and evaluate the model's performance in different contexts to enhance its predictive power.

E. Descriptive Statistics, Covariances, and Correlations

The descriptive statistics provide an overview of the mean, median, minimum, maximum, standard deviation, excess kurtosis, skewness, number of observations, and Cramér-von Mises test statistics for each variable in the UTAUT Model. Looking at the means, we can see that the average scores for siAverage, PeAverage, fcAverage, epAverage, ubAverage, eeAverage, and biAverage are relatively high, ranging from 4.387 to 4.520 on a scale of 1 to 5. This suggests that the respondents generally perceive positive levels of the respective constructs.

The covariances and correlations provide information about the relationships between the variables in the UTAUT Model. Looking at the covariances, there is an observance of a positive values between siAverage and fcAverage, siAverage and eeAverage, fcAverage and epAverage, and ubAverage and epAverage. On the other hand, there is also an observance of negative covariances between siAverage and epAverage, PeAverage and ubAverage, siAverage and biAverage, and eeAverage and biAverage. These values indicate the direction and strength of the relationships between the variables. Analyzing the correlations, similar patterns has been observed. For example, siAverage is positively correlated with fcAverage and eeAverage, while it is negatively correlated with epAverage and biAverage. PeAverage is negatively correlated with ubAverage and positively correlated with biAverage. These correlations provide insights into the interplay between the different constructs in the UTAUT Model.

The descriptive statistics, covariances, and correlations provide a preliminary understanding of the relationships and characteristics of the variables included in the UTAUT Model. Further analysis, such as structural equation modeling using Smart PLS, can help determine the significance and strength of these relationships and provide more robust insights into the factors influencing technology adoption and usage behaviors.

V. Discussion

The results of the study using the UTAUT Model to examine the factors influencing the dependent variable yielded several interesting findings. The summary coefficient analysis revealed that social influence (siAverage) and effort expectancy (eeAverage) had non-significant positive relationships with the dependent variable. This suggests that these factors may have a weak impact on the outcome. On the other hand, performance expectancy (PeAverage) displayed a marginally significant negative relationship, indicating a potentially weak negative influence. Facilitating conditions (fcAverage) and effort expended by users (epAverage) showed significant positive associations with the dependent variable, suggesting their importance in shaping the outcome. The other variables, biAverage and the intercept term, did not significantly affect the dependent variable. The results indicate that facilitating conditions and effort expended by users are the most influential factors in determining the outcome variable. Social influence, performance expectancy, and effort expectancy were not found to be significant predictors. However, it is important to note that the non-significant relationships should be interpreted with caution, as the sample size and effect sizes may influence the statistical significance.

The ANOVA results further supported the significance of the regression model. The F-test statistic indicated a significant relationship between the predictor variables and the dependent variable, with a low p-value. This suggests that the UTAUT Model, as represented by the included predictor variables, explains a significant portion of the variance in the dependent variable. The model demonstrated a good fit, providing evidence for the usefulness of the UTAUT Model in understanding the factors influencing technology adoption and usage behaviors.

The unstandardized coefficients provided insights into the magnitude and direction of the relationships. For example, a one-unit increase in fcAverage was associated with a 0.174-unit increase in the dependent variable. Similarly, a one-unit increase in epAverage was associated with a 0.245-unit increase in the dependent variable. These coefficients allow researchers and practitioners to understand the specific effects of each variable on the outcome.

Switching to standardized coefficients, researchers can assess the relative importance of the predictor variables. For instance, the standardized coefficient for epAverage was 0.246, indicating a stronger effect compared to other variables. These standardized coefficients help prioritize focus on variables with stronger or weaker effects.

The quality criteria analysis revealed that the UTAUT Model explained approximately 19.8% of the variance in the dependent variable. The R-square adjusted value, considering the complexity of the model, provided a more conservative estimate. The absence of significant autocorrelation in the model residuals and the lack of substantial multicollinearity among the predictor variables indicated good model fit. The results of the quality criteria and collinearity statistics suggest that the UTAUT Model provides a moderate level of explanation for the dependent variable, without significant multicollinearity among the predictor variables. However, the presence of some collinearity in condition index 6 should be taken into consideration. Researchers and practitioners can interpret these findings as an indication that the UTAUT Model, while explaining a modest proportion of the variance in the dependent variable, may still provide meaningful insights into the factors influencing technology adoption and usage behaviors. Future research should explore additional variables and evaluate the model's performance in different contexts to enhance its predictive power.

However, some collinearity was observed in condition index 6, suggesting a higher degree of collinearity among the variables in that index. Future research should consider addressing this issue and exploring additional variables to enhance the model's predictive power.

The descriptive statistics, covariances, and correlations provided a preliminary understanding of the relationships and characteristics of the variables in the UTAUT Model. These findings can guide further analysis using structural equation modeling to determine the significance and strength of the relationships.

A. Implications of the Findings

1) Influence of predictor factors: The results of the analysis indicate that facilitating conditions and user effort are the most influential factors in determining the adoption and utilization of the FIMS. Facilitating conditions, as measured by the fcAverage variable, had a positive and significant relationship with the dependent variable, indicating that the presence of supportive conditions, resources, and infrastructure plays a crucial role in promoting the adoption and usage of the FIMS. This finding aligns with prior research that emphasizes the importance of organizational support and resources in facilitating technology adoption and implementation [16].

Similarly, user effort, as measured by the epAverage variable, was found to have a positive and significant relationship with the dependent variable. This suggests that users' perceived effort in using the FIMS influences their adoption and utilization behavior. It implies that ease of use, user-friendly interface, and user training programs can contribute to enhancing technology adoption and usage behaviors. These findings are consistent with the technology acceptance literature, which emphasizes the significance of perceived ease of use and user experience in shaping technology adoption [16].

On the other hand, social influence, performance expectancy, and effort expectancy were not found to be significant predictors of FIMS adoption and utilization in the study. While this may seem contradictory to some prior research that has highlighted the importance of social influence and outcome expectations in technology adoption [16], it is important to note that the context of the study—specifically, the adoption and utilization of the FIMS in field incident management—may differ from previous studies that examined broader technology adoption contexts. The unique nature of field incident management systems and the specific tasks and requirements involved may contribute to different adoption and usage patterns.

2) Model fit and explained variance: The analysis of the model fit and explained variance provides insights into the goodness-of-fit of the UTAUT Model and its ability to explain the variance in the dependent variable. The findings indicate that the UTAUT Model explains a modest proportion of the variance in the adoption and utilization of the FIMS. The R-square value of 0.198 suggests that 19.8% of the variation in the dependent variable can be explained by the predictor factors included in the model. While this may appear relatively low, it is important to consider that technology adoption and usage behaviors are influenced by a multitude of factors beyond those captured by the UTAUT Model. Future research should explore additional variables and factors that may contribute to a more comprehensive understanding of technology adoption and utilization in the field incident management context.

Furthermore, the collinearity statistics indicate that there is no significant multicollinearity among the predictor variables in the UTAUT Model, except for the presence of collinearity in condition index 6. This suggests that the predictor variables are reasonably independent of each other and do not excessively overlap in their explanatory power. However, the presence of collinearity in condition index 6 should be considered and further investigated in future studies.

VI. Conclusions and Implications

A. Conclusion

This study identified several important findings regarding the factors impacting technology adoption and usage behaviors within the UTAUT Model. The study revealed that social influence and effort expectancy had no significant influence on the dependent variable, suggesting that social factors and perceived ease of use may not be substantial drivers of technology adoption and usage behaviors in this context. On the other hand, performance expectancy exhibited a moderately negative connection with the dependent variable, indicating that people's expectations about technology's performance may have a minor detrimental impact on their adoption and usage behaviors. Facilitating conditions and user effort, however, demonstrated significant positive relationships with the dependent variable, highlighting the importance of resource availability and effort exerted by users in determining technology adoption and usage behaviors. Behavioral intention and the intercept term did not have a significant effect on the dependent variable, indicating that they do not directly contribute to explaining heterogeneity in technology adoption and usage behaviors.

The study contributes to the theoretical understanding of technology adoption and usage behaviors by shedding light on the relative importance of different components within the UTAUT Model. It also highlights the need for further research to explore additional variables and validate the model's performance in different contexts, ultimately improving the understanding of technology adoption and usage behaviors.

B. Theoretical Implications

The theoretical implications of the conclusion provide insights into the relative importance of different factors within the UTAUT Model and highlight the need for further research to enhance the understanding of technology adoption and usage behaviors. The findings contribute to the refinement and development of theoretical frameworks and provide guidance for researchers and practitioners in understanding and promoting technology adoption and usage in various contexts.

C. Managerial Implications

The managerial implications of the conclusion guide managers in prioritizing facilitating conditions, encouraging user effort, contextualizing social influence and performance expectancy, continuously improving their understanding of adoption factors, and being mindful of collinearity and model fit considerations. By implementing these implications, managers can enhance the adoption and effective usage of technology within their organizations, leading to improved productivity, efficiency, and overall performance.

D. Limitations and Directions of Research

Conducting the study with a larger and more diverse sample would provide a more robust understanding of the relationships between the variables. The non-significant relationships found in the study should be interpreted with caution. The lack of significance may be influenced by the sample size or effect sizes, and further research with a larger sample is needed to confirm or refute these relationships. Additionally, the study focused on a specific context or population, which may limit the generalizability of the findings to other settings. Future research should consider the influence of contextual factors, such as cultural differences or industry-specific characteristics.

To address these limitations and further advance the field, future research directions can be pursued. One direction is to explore additional variables that could enhance the predictive power of the UTAUT Model. Factors like perceived risk, trust, or personal innovativeness could be included to provide a more comprehensive understanding of technology adoption and usage behaviors.

Moreover, conducting comparative studies across different contexts or populations would help validate the findings and identify potential variations in the relationships between the variables. This would contribute to the development of a more robust and contextually relevant model.

While the current study sheds light on the factors influencing technology adoption and usage behaviors, it is crucial to consider the limitations and pursue future research directions to strengthen the knowledge in this area. By addressing these limitations and expanding the scope of the investigation, researchers can make significant contributions to theory and provide more practical insights for managers and practitioners.

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REFERENCES

[1] Lu, Y., Papagiannidis, S., & Alamanos, E. (2021). Adding "things" to the internet: exploring the spillover effect of technology acceptance. Journal of Marketing Management, 37(7-8), 626–650. https://doi.org/10.1080/0267257x.2021.1886156.

[2] Altay, Ş., & İnan, G. G. (2022). An Empirical Study Of Technology Acceptance In Higher Education During Covid-19 Pandemic. Pazarlama ve Pazarlama Araştırmaları Dergisi. https://doi.org/10.15659/ppad.15.2.997751.

[3] Bommer, W. H., Rana, S., & Milevoj, E. (2022). A meta-analysis of eWallet adoption using the UTAUT model. International Journal of Bank Marketing, ahead-of-print(ahead-of-print). https://doi.org/10.1108/ijbm-06-2021-0258.

[4] A meta-analysis of the UTAUT model in the mobile banking literature: The moderating role of sample size and culture. (2021). Journal of Business Research, 132, 354–372. https://doi.org/10.1016/j.jbusres.2021.04.052.

[5] Analysis of User Acceptance towards Online Transportation Technology Using Utaut 2 Model: A Case Study in Uber, Grab and Go-Jek in Indonesia. (2017). International Journal of Science and Research (IJSR), 6(7), 1479–1482. https://doi.org/10.21275/art20175426.

[6] Savić, J., & Pešterac, A. (2019). Antecedents of mobile banking: UTAUT model. The European Journal of Applied Economics, 16(1), 20–29. https://doi.org/10.5937/ejae15-19381.

[7] Dwivedi, Y. K., Rana, N. P., Tamilmani, K., & Raman, R. (2020). A meta-analysis based modified unified theory of acceptance and use of technology (meta-UTAUT): a review of emerging literature. Current Opinion in Psychology, 36, 13–18. https://doi.org/10.1016/j.copsyc.2020.03.008.

[8] Hermanto, A. H., Windasari, N. A., & Purwanegara, M. S. (2022). Taxpayers' adoption of online tax return reporting: extended meta-UTAUT model perspective. Cogent Business & Management, 9(1). https://doi.org/10.1080/23311975.2022.2110724.

[9] Pradhan, B. B., & Mishra, S. S. (2019). An Investigation into the Adoption of Smartphone in India-UTAUT Model. Journal of Advanced Research in Dynamical and Control Systems, 11(10-SPECIAL ISSUE), 380–385. https://doi.org/10.5373/jardcs/v11sp10/20192817.

[10] Arfi, W. B., Nasr, I. B., Kondrateva, G., & Hikkerova, L. (2021). The role of behaviour in intention to use the IoT in eHealth: Application of the modified UTAUT in a consumer context. Technological Forecasting and Social Change, 167, 120688. https://doi.org/10.1016/j.techfore.2021.120688.

[11] Fan, W., Liu, J., Zhu, S., & Pardalos, P. M. (2020). Investigating the impacting factors for the healthcare professionals to adopt artificial intelligence-based medical diagnosis support system (AIMDSS). Annals of Operations Research, 294(1–2), 567–592. https://doi.org/10.1007/s10479-018-2818-y.

[12] Wang, H., Tao, D., Yu, N., & Qu, X. (2020). Understanding consumer acceptance of healthcare wearable devices: An integrated model of UTAUT and TTF. International Journal of Medical Informatics, 139, 104156. https://doi.org/10.1016/j.ijmedinf.2020.104156.

[13] Wang, H., Zhang, J., Luximon, Y., Qin, M., Geng, P., & Tao, D. (2022a). The Determinants of User Acceptance of Mobile Medical Platforms: An Investigation Integrating the TPB, TAM, and Patient-Centered Factors. International Journal of Environmental Research and Public Health, 19(17), 10758. https://doi.org/10.3390/ijerph191710758. Ong, A. K., Kurata, Y. B., Castro, S. A., De Leon, J. P., Dela Rosa, H. V., & Tomines, A. P. (2022). Factors influencing the acceptance of telemedicine in the Philippines. Technology in Society, 70, 102040. https://doi.org/10.1016/j.techsoc.2022.102040.

[14] Duarte, P., & Pinho, J. L. S. (2019). A mixed methods UTAUT2-based approach to assess mobile health adoption. Journal of Business Research, 102, 140–150. https://doi.org/10.1016/j.jbusres.2019.05.022.

[15] Ong, A. K., Kurata, Y. B., Castro, S. A., De Leon, J. P., Dela Rosa, H. V., & Tomines, A. P. (2022). Factors influencing the acceptance of telemedicine in the Philippines. Technology in Society, 70, 102040. https://doi.org/10.1016/j.techsoc.2022.102040.

[16] Venkatesh, V., Thong, J. Y., & Xu, X. (2012). Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology. Management Information Systems Quarterly, 36(1), 157. https://doi.org/10.2307/41410412.

[17] Tsourela, M., & Nerantzaki, D.-M. (2020). An Internet of Things (IoT) Acceptance Model. Assessing Consumer's Behaviour toward IoT Products and Applications. Future Internet, 12(11), 191. https://doi.org/10.3390/fi12110191.

[18] Puriwat, W., & Tripopsakul, S. (2021). Understanding Food Delivery Mobile Application Technology Adoption: A UTAUT Model Integrating Perceived Fear of COVID-19. Emerging Science Journal, 5, 94–104. https://doi.org/10.28991/esj-2021-sper-08.

[19] Leong, L.-Y., Hew, T.-S., Ooi, K.-B., & Dwivedi, Y. K. (2020). Predicting behaviour in online advertising with an SEM-artificial neural network approach. Expert Systems with Applications, 113849. https://doi.org/10.1016/j.eswa.2020.113849.

[20] Mwanza, E., Simalalo, M., & Simui, F. (2021). Virtual Learning for Persons with Visual Impairment: An Exploration of Learning Platform in a Home Environment from UTH Special School in Lusaka, Zambia. European Journal of Education and Pedagogy, 2(6),60–67. https://doi.org/10.24018/ejedu.2021.2.6.196.

[21] Sun, R., Zhang, S., Wu, N., Hu, J., Ruan, J., & Ruan, J. (2021). Willingness and Influencing Factors of Pig Farmers to Adopt Internet of Things Technology in Food Traceability. Sustainability, 13(16), 8861. https://doi.org/10.3390/su13168861.

[22] Fuad, A., & Hsu, C. (2018). UTAUT for HSS: initial framework to study health IT adoption in the developing countries. F1000Research, 7, 101. https://doi.org/10.12688/f1000research.13798.1.

[23] Faida, E. W., Supriyanto, S., Haksama, S., Suryaningtyas, W., Astuti, W., Nudji, B., & Hasina, S. N. (2022). The effect of performance expectancy and behavioral intention on the use of electronic medical record (EMR) in tertier hospital in Indonesia. International Journal of Health Sciences (IJHS), 1195–1205. https://doi.org/10.53730/ijhs.v6ns9.12729.

[24] Aria, R., & Archer, N. (2019b). The role of support and sustainability elements in the adoption of an online self-management support system for chronic illnesses. Journal of Biomedical Informatics, 95, 103215. https://doi.org/10.1016/j.jbi.2019.103215.

[25] Itasanmi, S. A. (2022). Determinants of the Behavioural Intention of Open Distance Learning Students to Use Digital Tools and Resources for Learning in Nigeria. Journal of Adult and Continuing Education, 147797142211356. https://doi.org/10.1177/14779714221135655.

[26] Wang, Y., Jin, L., & Mao, H. (2019). Farmer Cooperatives' Intention to Adopt Agricultural Information Technology—Mediating Effects of Attitude. Information Systems Frontiers, 21(3), 565–580. https://doi.org/10.1007/s10796-019-09909-x.

[27] Siregar, Z. A., Anggoro, S., Irianto, H. E., & Purnaweni, H. (2022). A Systematic Literature Review: UTAUT Model Research for Green Farmer Adoption. International Journal on Advanced Science,

Engineering and Information Technology, 12(6), 2485. https://doi.org/10.18517/ijaseit.12.6.15834.

[28] Bin-Nashwan, S. A., Shah, M. H., Abdul-Jabbar, H., & Al-Ttaffi, L. H. A. (2023). Social-related factors in integrated UTAUT model for ZakaTech acceptance during the COVID-19 crisis. Journal of Islamic Accounting and Business Research. https://doi.org/10.1108/jiabr-02-2022-0038.

[29] Ursavaş, Ö. F. (2022). Unified Theory of Acceptance and Use of Technology Model (UTAUT). Springer Texts in Education, 111–133. https://doi.org/10.1007/978-3-031-10846-4_6.

[30] Sulyani, A. C., Hariyanto, H., Larasati, N., & Shoofiyani, O. S. (2023, March 20). Farmer Readiness for Digital IoT Monitoring Apps Adoption based on UTAUT Model in West Java Province.

[31] Wu, G., & Gong, J. (2023). Investigating the intention of purchasing private pension scheme based on an integrated FBM-UTAUT model: The case of China. Frontiers in Psychology, 14. https://doi.org/10.3389/fpsyg.2023.1136351.

[32] Huang, Y. (2023). Integrated concepts of the UTAUT and TPB in virtual reality behavioral intention. Journal of Retailing and Consumer Services, 70, 103127. https://doi.org/10.1016/j.jretconser.2022.103127.

[33] Ningsih, S. K., Habibi, A., & Sofwan, M. (2023). The Influence Of The Unified Theory Of Acceptance And Use Of Technology (Utaut) Model On The Application Of Information And Communication Technology At Elementary Schools. Primary: Jurnal Pendidikan Guru Sekolah Dasar, 12(1), 190. https://doi.org/10.33578/jpfkip.v12i1.9544.