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A Well-Being Perspective on Drone Adoption by Iranian Potato Farmers

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Abstract

Traditional technology acceptance models primarily focus on behavioral factors, with limited exploration of well-being perspectives. This study examines the role of technology well-being, based on the PERMA framework, in shaping the intention and adoption of drone technology among potato farmers in western Iran. Using a descriptive-correlational survey design, path analysis of a systematic sample of 234 farmers revealed that intention, engagement, social relationships, meaning, and accomplishments significantly influence drone adoption, with path coefficients of 0.85 for intention and 0.38 for acceptance. Positive emotions, however, showed no significant effect. These findings highlight the critical role of well-being in technology acceptance, offering novel insights for precision agriculture. The results suggest that policymakers should prioritize persuasive strategies to enhance farmers' intentions, beyond merely promoting technology use. As one of the first studies to apply well-being theory to agricultural technology adoption, this research lays a foundation for future investigations, emphasizing technology well-being as a key driver of agricultural innovation.

Keywords: Drone technology, PERMA framework, Potato farmers, Precision agriculture, Technology well-being.

1.Introduction

Agricultural drones have transformed modern farming by enhancing productivity, operational efficiency, and sustainability (Rachmawati et al., 2021). Through precise field monitoring and targeted operations, drones can improve clean crop production and bolster food security (Shouji et al., 2021). In the potato trade, particularly the commercialization of sweet potatoes, these advancements play a pivotal role in improving farmers' livelihoods and fostering rural economic development (Oyebamiji et al., 2024). Factors such as farm size, access to credit, market proximity, and information availability significantly influence farmers' engagement in this trade. Given the heavy reliance on pesticides in potato cultivation, drone-based spraying offers a sustainable alternative, reducing pesticide use by 30–65% while maintaining or enhancing pest control efficacy (Patil et al., 2024). Consequently, drones represent a transformative tool for sustainable potato production and increased market competitiveness.

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Potatoes, recognized globally for their high yield per unit area, are a critical food source, producing more dry matter and protein per hectare than many major crops and serving as a nutrient-rich alternative to grains (Wijesinha-Bettoni & Mouillé, 2019; Devaux et al., 2014; Gustavsen, 2021). Unlike grains, their limited trade volume makes them a reliable option for food security, particularly in politically sensitive markets (Devaux et al., 2014). In Iran, the potato industry has seen significant growth from 1978 to 2023, with harvested areas expanding from 57,000 to 143,000 hectares (3% annual growth) and production rising from 735,000 to 5.5 million tons (5.5% annual growth), increasing yields from 8.12 to over 43 tons per hectare. In Kermanshah Province, Iran's fourth-largest potato producer, 6.3% of irrigated land is dedicated to potato farming, significantly contributing to local agricultural revenues. However, challenges such as excessive agrochemical use, climate change, outdated equipment, and declining water resources hinder productivity.

To meet rising demand and ensure food security, increasing potato production through innovative solutions like drone technology is essential. Drones enhance weed and pest management, boosting yields while promoting economic and environmental sustainability. Despite available infrastructure, drone adoption remains low in Kermanshah County, a key production hub (Fig. 1). Existing research has not sufficiently explored the reasons for this low adoption, particularly through a psychological lens. Traditional technology adoption models, such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), focus on factors like perceived usefulness and ease of use but often overlook psychological and well-being dimensions critical to rural agricultural contexts (Dissanayake et al., 2022; Blut et al., 2022). Factors such as trust in technology, prior experience, and risk attitudes, which significantly influence adoption, are underrepresented in these models (Dai & Cheng, 2022). This study addresses a critical gap in the literature by examining drone technology adoption among potato farmers in Kermanshah Province through the lens of well-being theory, specifically the PERMA model (Seligman, 2018). Unlike behavioral frameworks such as the Technology Acceptance Model (TAM) and the Theory of Planned Behavior (TPB), which focus primarily on utilitarian factors and have been widely applied in agricultural contexts, the PERMA model emphasizes psychological well-being, an underexplored dimension in agricultural behavioral economics. By employing PERMA independently, this research provides a novel theoretical framework that captures farmers' psychological and professional motivations, offering a distinct perspective beyond traditional models. Practically, the findings deliver actionable insights for policymakers and agricultural stakeholders to promote drone adoption, enhancing farm productivity and sustainability while fostering farmers' well-being.

Fig 1. Drone Technology in potato farming (Kermanshah, Iran).

2.The PERMA Model and Technology Well-Being

Traditional technology adoption models, such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), emphasize technical factors like perceived usefulness, ease of use, and performance expectations (Rouidi et al., 2022). However, these models often neglect psychological and well-being dimensions, limiting their applicability in complex settings like rural agricultural communities. Psychological and behavioral barriers significantly hinder technology adoption, particularly for innovations like drones (Lee et al., 2025). Integrating psychological frameworks with traditional models is thus essential for a comprehensive understanding of adoption dynamics. To address this gap, this study adopts the PERMA model (Seligman, 2018), a foundational framework in positive psychology, as its primary lens to explore farmers' acceptance of drone technology in potato field spraying in Kermanshah Province, Iran. PERMA comprises five dimensions—Positive Emotion, Engagement, Relationships, Meaning, and Accomplishment—which collectively offer a holistic perspective on how well-being shapes technology adoption (Ascenso et al., 2018). Unlike TAM and UTAUT, which prioritize utilitarian factors, PERMA captures farmers' psychological and professional motivations, making it particularly suited for rural agricultural contexts (Lenzenweger, 2004).

Positive Emotions, such as happiness and hope, are central to well-being and can foster technology adoption by creating favorable user experiences (Chisale & Phiri, 2022). Research shows that positive experiences with technology evoke emotions that enhance adoption intentions (Müller et al., 2016; Şahin et al., 2022). Engagement, defined as deep involvement in meaningful activities, is influenced by user experience quality, including challenge and perceived control (Lubis et al., 2019). Higher engagement is linked to stronger adoption intentions (Hussain et al., 2019). Relationships, a key PERMA component, emphasize social connections that facilitate adoption through collaboration and shared learning (Taylor, 2011). Meaning, reflecting purpose and life satisfaction, encourages positive attitudes toward technology use (Barachi et al., 2022). Accomplishment, tied to goal achievement, enhances motivation and adoption intent by fostering a sense of mastery (Umucu et al., 2022).

While PERMA is the primary framework, this study draws on insights from other behavioral models applied in Iran's agricultural sector to provide context. The Theory of Planned Behavior (TPB) highlights attitudes, norms, and control as adoption predictors (Valizadeh et al., 2018). The Value-Belief-Norm (VBN) theory underscores environmental values (Zobeidi et al., 2022), while Social-Cognitive Theory (SCT) emphasizes self-efficacy (Zola et al., 2022). By employing PERMA independently while acknowledging these frameworks, this study offers a novel theoretical contribution, integrating well-being into technology adoption research (Ryan et al., 2018). This approach not only enriches the theoretical discourse but also provides practical insights for promoting drone adoption in agriculture.

Based on this framework, the following hypotheses are proposed (see Figure 2):

- **H1**: Positive emotions toward drone technology significantly enhance farmers' intention to adopt it.
- **H2**: Engagement with drone technology positively influences farmers' intention to adopt it.
- **H3**: Social relationships in the context of drone technology positively impact farmers' intention to adopt it.
- **H4**: Meaning derived from drone technology is positively linked to farmers' intention to adopt it.
- **H5**: Accomplishments in using drone technology strengthen farmers' intention to adopt it.
- **H6**: The intention to use drone technology directly influences its actual adoption.

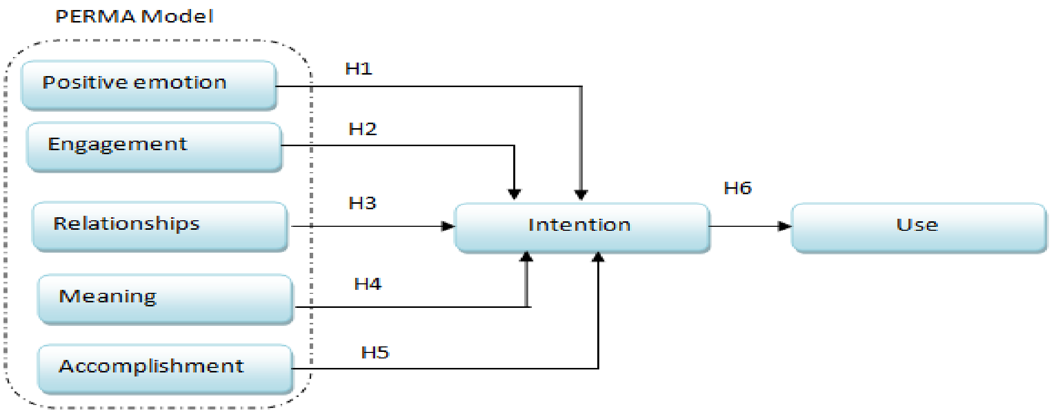

Fig. 2. PERMA-Based Model of Drone Technology Adoption.

3. Materials and Methods

3.1. Study Area

This study was conducted in Kermanshah Province, western Iran (Fig. 3), a kay agricultural region and Iran's fourth-largest potato producer. The province features a diverse climate, ranging from humid to semi-arid, with an average annual rainfall of 320 mm (1992–2014). In 2023, potato cultivation spanned 6,000–7,000 hectares, yielding approximately 350,000 tons, underscoring its critical role in food security and the rural economy, which relies heavily on agriculture and livestock. Predominant potato varieties include Agria, Marfona, Banba, and Burren. With an average yield of 50 tons/ha, the adoption of drone technology for precision spraying could enhance yields to 65–70 tons/ha, improving productivity and sustainability.

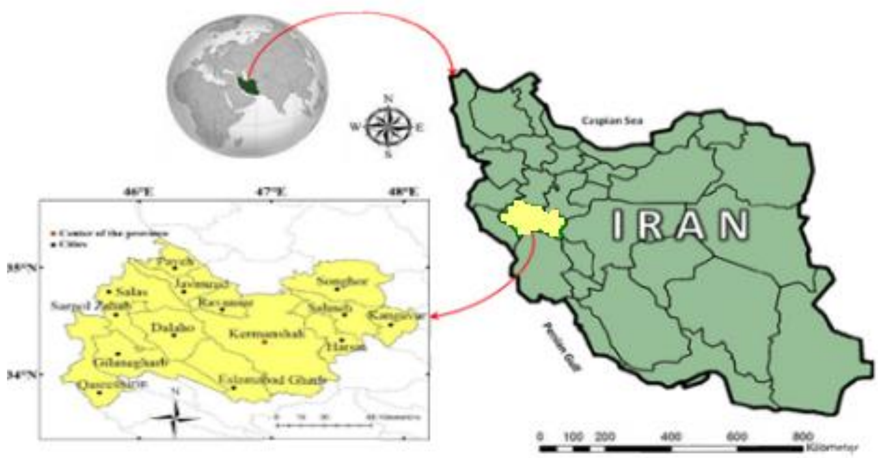

Fig 3. Locations of Kermanshah Province, Iran.

Research Design

This quantitative study employed a descriptive survey design to examine the model of drone technology acceptance in potato field spraying. Although technology acceptance has conventionally been explored through behavioral frameworks, there is a paucity of research examining its adoption through the lens of well-being theory.

Sampling Method

A systematic sampling approach was employed to select potato farmers in Kermanshah Province. This method proves particularly effective when the population is organized physically or in a listed format, and simple random sampling is impractical or labeling all units is challenging (Hankin et al., 2019). The study targeted the entire population of 596 potato farmers, as documented by the Statistical Center of Iran (2019). Based on Krejcie and Morgan's (1970) sample size table, a sample of 234 farmers was determined (n = 234). Notably, the study focused exclusively on farmers without prior experience using drones on their farms, positioning the research within an ex-ante analytical framework (Thurow et al., 1997).

Data Analysis Method

Data were collected through a self-administered questionnaire comprising two sections: (1) Demographics and Professional Characteristics (14 items) and (2) PERMA Model-Based Assessment (21 items), adapted from Ascenso et al. (2018), to evaluate farmers' perceptions of drone technology. The instrument's validity was established through review by a panel of experts. A pilot study involving 30 farmers from Miandarband, Kuzaran, and Sarabniloofar—villages excluded from the final sample—was conducted to assess reliability. Study variables and composite reliability (CR) coefficients are presented in Table 1.

Data analysis was performed using SPSS 16 and SmartPLS 3. Preliminary checks for normality, outliers, and multicollinearity were conducted to ensure data validity, with all metrics meeting acceptable thresholds, consistent with Subhaktiyasa (2024). Partial Least Squares Structural Equation Modeling (PLS-SEM) was employed due to its robustness in analyzing complex models and suitability for smaller sample sizes (Hair & Alamer., 2022). The conceptual model incorporated latent variables (reflective and/or formative constructs), with relationships examined using SmartPLS 3.

The measurement model's validity and reliability were evaluated through composite reliability (CR), convergent validity (Average Variance Extracted, AVE), and discriminant validity (Fornell-Larcker criterion), all of which met established benchmarks (Hair & Alamer., 2022). The structural model was assessed by examining path coefficients, R^2 values, and the significance of relationships via a bootstrapping procedure.

Table 1. Survey Measures and corresponding questionnaire items.

Measure	Description	Number of items	CR
Positive emotion (Pe)	Feelings of happiness, hope, and enjoyment in using drone technology (1= very low, 5= very high)	3	0.87
Engagement (En)	Deep involvement in meaningful and challenging activities (1= very low, 5= very high)	5	0.87
Relationships (Re)	User's understanding and long-term commitment to drone technology (1= very low, 5= very high)	4	0.95
Meaning (Me)	Sense of purpose and career significance derived from drone technology use (1 = strongly disagree, 5= strongly agree)	3	0.91
Accomplishment (Ac)	Farmers' sense of success in achieving professional goals through drone technology (1 = strongly disagree, 5= strongly agree)	3	0.84
Intention (In)	Farmer's decision and willingness to adopt drone technology (1= strongly disagree, 5 = strongly agree)	3	0.94
Use (U)	Practical application of drones in farm management (1= strongly disagree, 5= strongly agree)	4	0.81

4. Findings

4.1. Demographic and Socioeconomic Characteristics

The respondents in this study had a mean age of 46.2 years (SD = 15.3), ranging from 24 to 70 years, with 96.6% male and 3.4% female. Most respondents (89.7%) were married, with an average household size of four members. Educationally, 50.2% held a bachelor's degree or higher, 30.9% had a diploma, and 19.9% had education below the diploma level. Occupationally, 90.6% were farmers, with 93.6% self-employed and 6.4% employed. The mean agricultural experience was 22.5 years (SD = 11.24), while potato cultivation experience averaged 2.5 years (SD = 2.52).

The average income from potato cultivation was 652.4 million Iranian Rials per hectare (SD = 21.61), with cultivation costs averaging 216.0 million Iranian Rials per hectare (SD = 9.36). Most farmers (93.6%) were native to Kermanshah Province, with a negligible proportion being non-native. Respondents owned an average of 8.28 hectares of total land, including 4.37 hectares of dry land, 4.17 hectares of irrigated land, and 1.43 hectares of potato fields. Over 90% of land was personally owned, with a small fraction leased or jointly owned. The average pesticide cost for pest and weed control was 17.45 million Iranian Rials per hectare.

4.2. Evaluation of the Drone Technology Acceptance Model

Confirmatory factor analysis (CFA) was conducted to evaluate the fit, validity, and reliability of the PERMA-based model for drone technology acceptance in potato field spraying. The model assessed dimensions including need, positive emotions, engagement, social relationships, meaning, accomplishments, and frequency of drone use. After removing one indicator from social relationships (Re5), the model demonstrated a good fit. Goodness-of-fit indices, correlation coefficients, and summary results are presented in Tables 2, 3, and 4.

Table 2. Goodness-of-Fit Indices for the PERMA-Based Drone Technology Acceptance Model.

Fit index	SRMR	D_LS	D_G	NFI	RMS_Theta
Recommended value	< 0.10	> 0.05	> 0.05	> 0.80	≤ 0.12
Estimated value	0.097	3.07	2.114	0.85	0.11

All factor loadings were statistically significant ($p < 0.05$), confirming unidimensionality. Composite reliability (CR > 0.80) demonstrated strong internal consistency, while convergent validity (AVE > 0.50) indicated that the indicators effectively captured variance in their respective constructs. Discriminant validity was also confirmed, as the square root of AVE for each construct exceeded its correlations with other constructs, ensuring construct distinctiveness (Table 3).

Table 3. Factor Loadings and Reliability Metrics for the PERMA-Based Drone Acceptance Model.

Latent variables (Measures)	Observed variables (Items)	factor loadings (β)	t	CR	AVE
Pe	Pe1	0.60	**5.11	0.87	0.70
	Pe2	0.92	**69.56		
	Pe3	0.94	**114.69		
	En1	0.85	**64.64		
En	En2	0.84	**39.58		
	En3	0.81	**20.67	0.87	0.59
	En4	0.80	**21.27		
	En5	0.43	**4.09		
	Me1	0.94	**153.35		
Me	Me2	0.93	**76.26	0.95	0.87
	Me3	0.91	**98.60		
	Re1	0.91	**80.30		
Re	Re2	0.89	**49.40	0.91	0.78
	Re3	0.87	**44.02		
	Re4	0.22	*2.02		
	Ac1	0.96	**138.48		
Ac	Ac2	0.90	**65.32	0.84	0.61
	Ac3	0.89	**39.17		
In	In1	0.92	**76.15		
	In2	0.92	**82.12	0.94	0.85
	In3	0.93	**86.76		
U	U1	0.89	**76.26		
	U2	0.87	**98.60	0.81	0.65
	U3	0.74	**44.02		
	U4	0.71	**69.56		

** Significantly at 1% error level and * significantly at 5% error level.

Based on the results presented above, the proposed measurement model for drone technology acceptance in potato field spraying, comprising seven primary latent constructs, is a suitable framework for conducting analyses in this study.

Table 4. Discriminant Validity of the PERMA-Based Drone Acceptance Model (Fornell–Larcker Criterion).

	Ac	En	In	Me	Pe	Re	U
Ac	**0.91**						
En	0.76	**0.86**					
In	0.87	0.82	**0.92**				
Me	0.87	0.76	0.89	**0.93**			
Pe	0.54	0.47	0.52	0.51	**0.83**		
Re	0.72	0.71	0.78	0.77	0.68	**0.78**	
U	0.51	0.57	0.62	0.61	0.43	0.65	**1**

Note: The numbers of the table diameter are root AVE and the numbers below diameter are the correlation coefficients between the variables.

Following validation of the measurement model through confirmatory factor analysis, path analysis was employed to test the research hypotheses within the proposed conceptual framework for drone technology acceptance in potato field spraying. The path model, including standardized factor loadings (Fig. 4), significant path coefficients (Fig. 5), and a summary of results (Table 5), is presented to illustrate the structural relationships in the drone technology acceptance model.

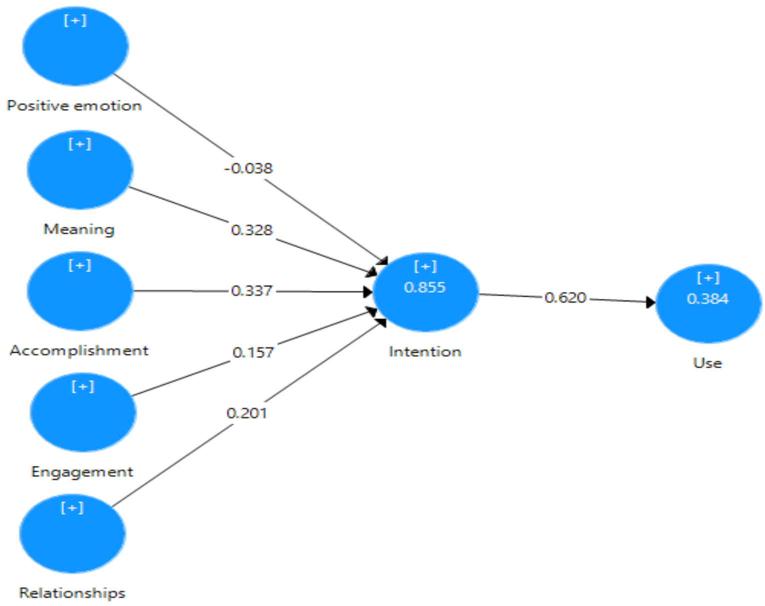

Fig 4: PERMA-Based Drone Acceptance Model with Standardized Factor Loadings.

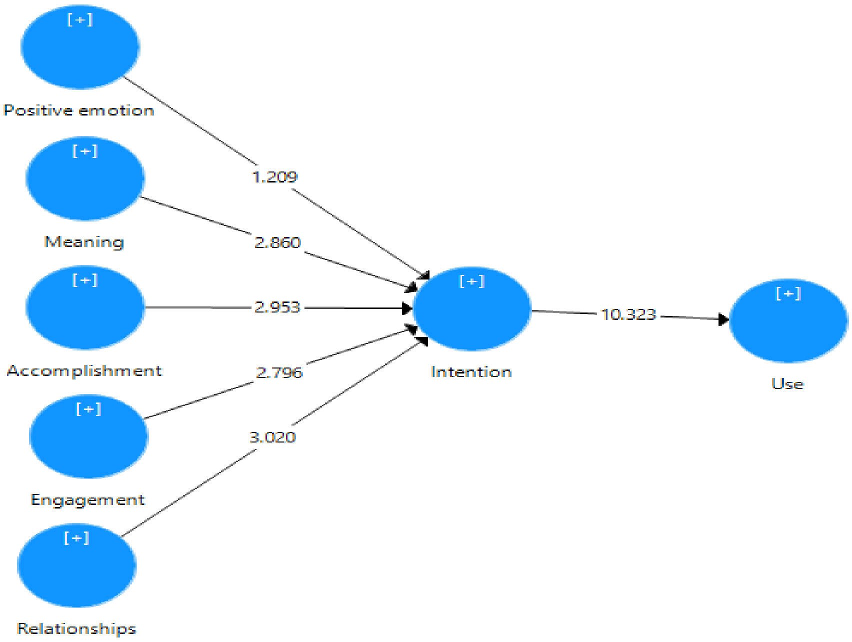

Fig 5: PERMA-Based Drone Acceptance Model with Significant Path Coefficients.

The path analysis (Table 5) revealed that intention, engagement, social relationships, meaning, and accomplishments significantly influenced drone technology acceptance in potato field spraying ($p < 0.01$), while positive emotions showed no significant effect. The coefficient of determination (R^2) indicated that these factors strongly predicted acceptance ($R^2 = 0.38$) and intention to use drones ($R^2 = 0.85$). Effect size analysis (f^2) highlighted a strong effect of intention, moderate effects of engagement, social relationships, meaning, and accomplishments, and a weak effect of positive emotions. The high predictive relevance (Q^2) confirmed the model's effectiveness in forecasting both intention and acceptance, supporting its applicability for policy development to enhance drone adoption.

Table 5: Path Analysis Results for the PERMA-Based Drone Acceptance Model.

Latent variables		Direct effect		Indirect effect		Total effect		2f	R2	Q2
		t	β	t	β	t	β			
Use of drone technology	Intention	0.62	**10.32	-	-	-	-	0.62		
	Positive emotion	-	-	-0.02	1.21	-0.02	1.21	-		
	Engagement	-	-	0.09	**2.84	0.09	**2.84	-		
	Relationship	-	-	0.12	**2.74	0.12	**2.74	-	0.38	0.37
	Meaning	-	-	0.20	**2.71	0.20	**2.71	-		
	Accomplishment	-	-	0.20	**2.89	0.20	**2.89	-		
Intention	Positive emotion	-0.03	1.20	-	-	-0.03	1.20	0.01		
	Engagement	0.15	**2.79	-	-	0.15	**2.79	0.04		
	Relationship	0.20	**3.02	-	-	0.20	**3.02	0.08	0.85	0.72
	Meaning	0.32	**2.86	-	-	0.32	**2.86	0.09		
	Accomplishment	0.33	**2.95	-	-	0.33	**2.95	0.17		

** Significantly at 1% error level.

5. Discussion

This study demonstrates that intention, engagement, social relationships, meaning, and accomplishments significantly influence drone adoption for pesticide spraying in potato farming, while positive emotion have no significant effect. These findings position technology well-being, as conceptualized through the PERMA framework, as a pivotal construct in technology adoption, extending beyond traditional models like Technology Acceptance Model (TAM), which focus primarily on perceived usefulness and ease of use. By employing the PERMA framework independently, this research offers a novel theoretical contribution, extending the application of technology well-being to emerging technologies like drones.

Engagement is a key driver of drone adoption, with farmers more likely to adopt drones when perceived as useful, efficient, and beneficial to their agricultural practices. This aligns with prior studies (Lee et al., 2020; Taoufik, 2020), which emphasize perceived value and expectancy as core determinants of adoption intentions. In traditional farming systems, repetitive and physically demanding tasks often lead to fatigue and reduced motivation among farmers, including potato growers. The introduction of drone technology can transform agriculture into a more engaging and meaningful activity, enhancing productivity and sustainability (Nguyen et al., 2024). These findings are globally relevant, as engagement-driven strategies can promote drone adoption in precision agriculture across diverse regions.

Social relationships significantly shape adoption, both directly and indirectly, through supportive networks and peer influence. Research (Irzan et al., 2021; Koelle et al., 2018) highlights that social connections foster technology adoption by creating enabling environments. This is particularly relevant in collectivistic agricultural societies, such as those in South Asia, Latin America, and rural Europe, where peer adoption and knowledge sharing reduce perceived risks (Antolini et al., 2018; Pilay et al., 2020). Moreover, social networks and brand identification (Stephan et al., 2010; Tien-chi et al., 2022) reinforce positive attitudes toward technology across diverse cultural contexts, enhancing the global applicability of these findings.

The role of meaning underscores that farmers who align drone use with their professional aspirations are more inclined to adopt the technology. This is consistent with prior research (Rao, 1996; Yu-Hsin et al., 2020), which highlights goal alignment as a key driver of technology acceptance. Drones, by providing precise data and enabling rapid decision-making, enhance farmers' knowledge and control over their fields, thereby fostering a sense of purpose and professional advancement (McCarthy et al., 2024). This pattern is applicable to farming communities worldwide, where technologies that align with professional goals can drive adoption.

Accomplishments, particularly economic benefits, strongly predict drone adoption, as farmers prioritize technologies that increase yields, reduce costs, and enhance profitability. This is supported by studies (Chavdhari et al., 2001; Teyagrajan & Vasantakomar, 2009; Zhang et al., 2015), which emphasize economic incentives as universal drivers of technology adoption. Drones facilitate precise pesticide application, improving productivity and product quality, which in turn enhances job satisfaction and a sense of achievement among farmers (Olson & Anderson, 2021). These findings are relevant to both smallholder and large-scale farming systems globally.

Contrary to studies emphasizing the role of positive emotions in technology adoption (Mansoor et al., 2020; Suur-Inkeroinen et al., 2011; Tsaur et al., 2015), this research found no significant emotional influence. Farmers without direct drone experience may struggle to associate positive emotions like joy or hope with the technology, as supported by recent evidence (Suvittawat, 2024). Instead, perceived usefulness, economic benefits, and social influence are prioritized, particularly in resource-limited contexts (Acıbuca, 2024; Waris et al., 2022; Zhang & Li, 2005). In wealthier agricultural systems, such as those in Europe or North America, where financial risks are lower, positive emotions may play a more prominent role (Djamasbi et al., 2010).

Despite the strong path coefficient (0.85) between intention and adoption, practical barriers such as cost, training, and access—though not assessed in this study—may hinder adoption. These barriers are prevalent globally, particularly in developing nations with limited infrastructure. Future research should explore solutions like public-private partnerships or subsidies to enhance drone adoption in regions such as South Asia, Africa, and Latin America. By contextualizing these findings within a global framework, this study advances the literature on agricultural technology adoption. The integration of well-being constructs through the PERMA framework provides a novel perspective, informing policies and practices for both smallholder and large-scale farming systems worldwide.

6. Implications

6.1 Theoretical Implications

The findings provide empirical validation for drone technology adoption in potato farming, confirming the relevance of psychological well-being in adoption models. By employing the PERMA framework independently, this study offers a novel theoretical contribution, extending the application of technology well-being to emerging technologies like drones. The limited use of the PERMA model in prior technology adoption research underscores the study's role in expanding the literature by incorporating diverse perspectives on acceptance and influential factors. Incorporating technology well-being into adoption frameworks broadens the theoretical scope and highlights its critical role in shaping farmers' intentions and behaviors.

6.2 Practical and Policy Implications

Policymakers often prioritize psychological factors in designing technology adoption strategies. This study highlights the equal importance of technology well-being. To enhance drone acceptance, planners should incorporate well-being principles into adoption programs, ensuring both psychological and well-being factors are addressed in policy frameworks. This approach can strengthen strategies for promoting sustainable agricultural innovations in rural settings.

7. Limitations

This study has several limitations. First, the limited literature on technology well-being restricted comparative analyses, constraining the depth of discussion despite contributing to the study's originality. Second, reliance on quantitative methods may not fully capture the complexities of technology well-being. Future research should employ qualitative approaches to explore nuanced dimensions and refine the PERMA framework. Third, as many potato growers lacked direct drone experience, the study focused on the prospective role of technology well-being. Retrospective studies comparing early adopters and new users could enhance model validity. Fourth, the focus on farmers without prior drone experience may limit the generalizability of findings. Future studies should adopt ex-post or mixed methods to compare perceptions and behaviors of farmers with and without drone experience. Fifth, the potential mediating role of financial concerns in the relationship between positive emotions and adoption behavior was not empirically tested. Future research could address this gap through mediation analysis. Finally, due to time and budgetary constraints, this study examined only the PERMA framework independently, without integration with established models like TAM or UTAUT. Future research should combine PERMA with these frameworks to provide a more comprehensive understanding of technology adoption.

8. Conclusion

Technology well-being, though a novel concept, emerges as a critical factor in drone technology adoption. While prior agricultural studies have largely overlooked this aspect, this research underscores its pivotal role in shaping acceptance behaviors. Incorporating technology well-being into existing adoption models could enhance their relevance and applicability. Financial barriers remain a significant obstacle to drone adoption, particularly in developing countries. Government interventions, such as financial support and policy incentives, are essential to promote adoption. Addressing these challenges will strengthen the technology well-being model and lay a foundation for future research in this evolving field.

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