Agricultural & Rural Studies

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Investigating Farmers' Intention to Adopt Renewable Energy Technology for Farming: Determinants of Decision Making in Northern Ghana

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Abstract: Integrating renewable energy into agricultural practices can result in environmental and economic benefits. In Ghana, renewable energy resources that can support agronomic activities include solar energy and biomass. Although policies and interventions that promote Ghanaian renewable energy development and implementation currently exist, it is not yet understood which factors motivate farmers to adopt renewable energy technologies within the country's agricultural sector. This research aimed to identify which psychological and economic factors influence Northern Ghanaian farmers' intention to adopt renewable energy technology within agriculture. A survey was administered to farmers (n = 418) in Lawra Municipality in Northern Ghana, where farming represents the main source of income. Structural Equation Modelling was applied to test and validate an adapted theoretical model (the Decomposed Theory of Planned Behaviour) to identify which factors are associated with farmers' likelihood to adopt renewable energy technology. Attitude, Perceived Behavioural Control, Perceived Usefulness, Perceived Ease of Use, Compatibility, Risk, Peer and External Influences, Self-efficacy, Resource-Facilitating Conditions, and Technology-Facilitating Conditions were positive and significant factors influencing farmers' intention to adopt renewable energy technology. However, subjective norms did not positively predict farmers' intentions. The results suggest that to ensure the widespread adoption of renewable energy in Ghanaian agriculture, policies and interventions could usefully align with the psychological attributes of farmers. Policymakers should develop and implement appropriate policies to encourage sustainable technology adoption in agriculture, including tax and credit subsidies and green financing frameworks to increase support for farmers to adopt renewable energy technology.

Keywords: renewable energy; technology; Decomposed Theory of Planned Behaviour; lower-to-middle-income country; LMIC; agriculture

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Citation: Karbo, R. T.- viel, Frewer, L. J., Areal, F. J., Boaitey, A., Jones, G., & Garrod, G. (2025). Investigating Farmers' Intention to Adopt Renewable Energy Technology for Farming: Determinants of Decision Making in Northern Ghana. *Agricultural & Rural Studies*, *3*(1), 25. https://doi.org/10.59978/ar03010003

Received: 23 September 2024
Revised: 24 October 2024
Accepted: 30 December 2024
Published: 28 February 2025

1. Introduction

Since the ratification of the Kyoto Protocol and the Paris Agreement, many countries have prioritised sustainable energy technology and developed and implemented policies aimed at decreasing carbon emissions and improving national energy security (Pestisha et al., 2023). Renewable energy is important from an environmental perspective as it utilises resources that can generate clean energy with minimal environmental effects (Adams & Nsiah, 2019; Jin & Kim, 2018; Wesseh & Lin, 2017). Renewable energy can contribute to global energy requirements given its regenerative characteristics, including solar, wind, biomass, hydro, geothermal, wave and tidal energy sources (Chel & Kaushik, 2011). In addition to the environmental benefits, renewable energy is associated with stable market conditions when compared to, for example, the volatility in prices of fossil fuels such as crude oil (Ali et al., 2012; Pestisha et al., 2023) and is more likely to ensure energy security (Sotnyk et al., 2021). However, the potential benefits across industry different sectors cannot be realised unless stakeholders and end-users widely adopt renewable energy. It is important to understand the socio-economic factors which determine whether farmers will adopt new technologies with the potential to deliver environmental benefits into their agricultural practices. This research used a modified version of the Decomposed Theory of Planned Behaviour to identify which psychological and economic factors influence Northern Ghanaian farmers' intention to adopt renewable energy technology within agriculture. Although the use of sustainable energy in agriculture has been identified as important in Ghanaian policy (Karbo et al., 2022), adoption by stakeholders within the sector has been slow.

Energy is needed in economically influential sectors, including agriculture. Agriculture directly supports food production and so is needed for national and global development (Best, 2014; Lawal, 2023). Due to increased mechanisation within the sector, agriculture has become increasingly dependent on energy and has been estimated to contribute between 14 to 30 percent of global greenhouse gas (GHG) emissions (Khan et al., 2018; Lenka et al., 2015; Liu et al., 2017b; Richards et al., 2018). The manufacture and application of agricultural inputs, use of fossil-fuelled farm machinery, poor practices in land preparation and agronomic activities, and livestock production represent significant contributors to GHG emissions (Bell et al., 2014; Bellarby et al., 2013; Blandford & Hassapoyannes, 2018; Lenka et al., 2015). This trend will continue if the current level of energy use intensity in agriculture is increased in line with greater agronomic mechanisation and automation which is required to deliver future food security requirements (Lenka et al., 2015; Liu et al., 2017a). Food demand is projected to increase based on increasing population, and this will potentially drive the increase in energy use in agriculture because of the need to increase agricultural efficiency through technological applications which may use more energy (Harvey & Pilgrim, 2011; Röös et al., 2017).

Renewable energy utilisation is needed to decrease the agricultural sector's carbon emissions and ensure energy self-sufficiency for farmers and other agricultural value chain actors (Abaka et al., 2017; Jebli & Youssef, 2017; Pestisha et al., 2023). There is evidence that renewable energy resources can support future agricultural energy needs and, at the same time, promote sustainable agricultural production (Martinho, 2018; Smith & Gregory, 2013). Renewable energy can be used to support farm-based activities such as generating electricity for lighting, powering water pumps, providing heating in greenhouse farming, drying, heating and cooling for storage purposes on farms (Abaka et al., 2017; Ali et al., 2012; Bayrakcı & Koçar, 2012). Agriculture can also create raw materials in the form of biomass resources (i.e., crops/livestock residue/bioenergy crops) that can support energy generation to be used for various agricultural activities (Best, 2014). Thus, as the reliability of the renewable energy supply is improved, alternative income sources can be generated for farmers and farms (Fami et al., 2010). Given that agronomic, social, and economic benefits can be provided by renewable energy sources, countries and stakeholders (e.g., policymakers, farmers, and other supply chain actors) need to develop appropriate approaches to optimise the full potential of renewable energy resources and how these are applied in the agricultural sector (Dulal et al., 2013; Elahi et al., 2022).

Governments and interested stakeholder groups have promoted the use of innovative agricultural technologies, including renewable energy technologies (e.g., solar energy and use of biomass), to farmers for adoption into their agricultural practices. It is expected that when farmers start to adopt renewable energy technologies, agronomic practices will transition from those using labour-intensive manual methods to those integrating mechanised farming due to the increased availability of energy, enabling farmers to expand farming acreages, production yields, and household income (Aryal et al., 2021; Sims & Kienzle, 2017). For example, renewable energy technology can support agronomic practices in relation to land preparation activities using biomass energy inputs such as organic fertilisers to improve soil fertility and solar water pumps to irrigate crops (Ayamga et al., 2015; Stock et al., 2023).

In Ghana, farmers are encouraged by the government including the Ministry of Food and Agriculture (Investment for Food and Jobs), Ministry of Energy (Ghana Renewable Energy Master Plan), Ministry of Environment, Science, Technology, and Innovation (National Climate Change Policy) and interested stakeholder groups (such as Peasant Farmers Association of Ghana, Centre for Indigenous Knowledge and Organisational Development, FARA, etc) to adopt innovative agricultural technologies, including renewable energy technology, to improve their farming productivity sustainably. At present, there is evidence that renewable energy technology adoption in Ghana in the agricultural sector is low, and identification of factors which may accelerate, or act as barriers to, farmers' adoption behaviours to renewable energy technologies (Asiamah et al., 2022; Karbo et al., 2022).

Previous research has identified factors which may influence farmers' adoption behaviours in relation to new technologies (e.g., see Kabwe et al., 2009; Mapemba et al., 2013; Mogaka et al., 2014; Mukherji et al., 2017; Mwakaje, 2008; Nyamwena-Mukonza, 2012; Obiero et al., 2019; Putra et al., 2019). For example, the cost of adopting technology, technology compatibility with existing agricultural practices, peer influence, perceived risk of adoption, enhanced time farming time, and extension services to educate farmers are some of the factors identified to influence farmers' technology adoption behaviour (Ambali et al., 2021; Cheteni et al., 2014; Makate, 2020; Olumba et al., 2024; Tran-Nam & Tiet, 2022). Understanding how these factors influence farmers' technology adoption behaviours can help researchers, policymakers, and other non-farmer stakeholders develop interventions to increase farmers' technology adoption (Borges et al., 2014).

This research aims to understand which psychological and perceived economic determinants influence farmers' intention to adopt renewable energy technology in Northern Ghana agriculture. Researchers have applied various theoretical approaches to understand the psychological and perceived economic determinants of farmers' technology adoption behaviours including the Diffusion of Innovation theory, the Theory of Planned Behaviour, the Expected Utility Theory, and the Decomposed Theory of Planned Behaviour (Musungwini et al., 2022; Nyairo et al., 2022; Sileshi et al., 2019; Zeweld et al., 2017b).

The Decomposed Theory of Planned Behaviour was used in this research to assess which psychological predictors may affect farmers' intention to adopt renewable energy in the context of Northern Ghana. The Decomposed Theory of Planned Behaviour was identified as a suitable theoretical approach to predict farmers' behavioural intentions to adopt renewable energy in agriculture, as previous research has validated its application in LMICs to assess agricultural technology adoption (Table 1). Application of the Decomposed Theory of Planned Behaviour provides evidence for policymakers to enable them to consider psychological factors in the development of policies and interventions aimed at improving the adoption of renewable energy technology for farming by farmers. From a theoretical perspective, the research provides evidence regarding the validity of the theory in the context of the prediction of farmers' adoption behaviours in relation to renewable energy in the context of Ghana, and potentially in a broader LMIC context.

Table 1. Selected studies in LMICs which have applied the Decomposed Theory of Planned Behaviour in agriculture.

	Aims of the Research	Country (or Countries)	Main Results	Reference
1.	To examine behavioural factors affecting the adoption of manuring of smallholder mature rubber cultivations.	Sri Lanka	A positive relationship existed between compatibility and attitude, perceived usefulness and attitude, and perceived ease of use and attitude. No relationship between relative advantage and attitude was observed.	Gunarathne et al. (2021)
2.	To investigate socio-technological factors influencing smallholder farmers' choices of agroforestry technologies in the eastern highlands of Uganda.	Uganda	The number of tree species preferred by farmers in agroforestry, and the perceived value of agroforestry were the most important factors that determined farmers' decision to adopt agroforestry technologies.	Kalanzi et al. (2021)
3.	To explore factors that influenced farmers' intention to adopt sustainable agriculture practices for coffee farming in Vietnam.	Vietnam	Farmers' intention to adopt sustainable agricultural practices was influenced by perceived social pressure, the perception of climate change, and the perceived ability to perform sustainable agriculture.	Nguyen & Drakou (2021)
4.	To understand the behavioural intentions of smallholder farmers in relation to the adoption of mechanised conservation agriculture.	Zambia	Positive attitude towards, and perceived behavioural control over, increased farmers' intention to adopt mechanised conservation agriculture.	Omulo et al. (2024)
5.	To understand smallholder farmers' behavioural intentions to adopt sustainable agriculture practices in Ethiopia.	Ethiopia	Positive attitudes and normative issues such as technical training, extension service, and social capital explain farmers' behavioural intention to adopt sustainable agricultural practices.	Zeweld et al. (2017b)

2. Research Model and Hypotheses Development

2.1. The Decomposed Theory of Planned Behaviour

The Decomposed Theory of Planned Behaviour was initially developed by Taylor and Todd (1995a) as an extension of the Theory of Planned Behaviour. Similarly, the Decomposed Theory of Planned Behaviour assumes that a behavioural intention is likely to lead to an adoption behaviour, and that interacting psychological constructs (Attitude, Subjective Norms, and Perceived Behavioural Control) predict behavioural intention (Alomary & Woollard, 2015; Shao et al., 2022). In addition to building on the Theory of Planned Behaviour, the Decomposed Theory of Planned Behaviour unifies constructs from the Technology Acceptance Model (Davis, 1989), the Theory of Planned Behaviour and the Diffusion of Innovations Theory (Ajzen, 1991). Specifically, the Decomposed Theory of Planned Behaviour includes the constructs "perceived Ease of Use" and "Perceived Usefulness" from the Technology Acceptance Model as components of "Attitude" (Davis, 1989). Perceived Compatibility, derived from the Diffusion of Innovation Theory, is also assumed to contribute to attitude (Rogers, 2003).

The Theory of Planned Behaviour has been criticised as it assumes that attitudes predict behaviours, which in turn are predicted by Subjective Norms and perceived behavioural control (Taylor & Todd, 1995a). The Decomposed Theory of Planned Behaviour addresses this criticism by decomposing the Attitude, Subjective Norms, and Perceived Behavioural Control constructs further. According to Fishbein and Ajzen (1977), attitude as a construct refers to the sentiments (positive or negative) an individual develops regarding whether to perform a particular behaviour. Subjective norms are the social pressures that are perceived to be influential, and that can influence an individual's intention to adopt or reject technology. The perceived behavioural control construct refers to the perceived ease or difficulty in performing an adoption behaviour regarding a technology.

The underlying factors that determine the three main constructs of the Decomposed Theory of Planned Behaviour. Attitude is determined by Ease of Use, Perceived Usefulness, and Compatibility. Subjective Norms are influenced by Peer and External Influences. Perceived Behavioural Control is influenced by Self-efficacy, Resource-Facilitating Conditions, and Technology-Facilitating Conditions. Table 1 provides examples of the application of the Decomposed Theory of Planned Behaviour to agriculture in LMIC countries.

2.2. Development of Hypotheses

The hypotheses were developed from the Decomposed Theory of Planned Behaviour where three primary constructs are proposed to predict Behavioural Intention: Attitude, Subjective norms, and Perceived Behavioural Control. The following hypotheses are proposed:

- H1: A positive Attitude will increase intention to adopt a renewable energy technology in farming.
- H2: Positive Perceived Subjective Norms will increase intention to adopt renewable energy technology for farming.
- H3: Higher perceived Behavioural Control will increase intention to adopt a renewable energy technology for farming.

The three primary constructs, Attitude, Subjective Norms, and Perceived Behavioural Control are decomposed into sub-constructs in the Theory (i). Three sub-constructs contribute to Attitude: These are Perceived Ease of Use, Perceived Usefulness, and Compatibility. In this research, perceived ease of use assessed the extent to which a new renewable energy technology was perceived to be convenient to understand and operate. Perceived usefulness measures the individual's expectation that (e.g.) a new technology improves the outcomes of a task or activity. Perceived compatibility assesses the suitability of (e.g.) a new technology relative to an existing technology or practice. Therefore, it is assumed that a farmer is more likely to adopt a renewable energy technology for farming if its application is perceived to be easy to understand and operate. Similarly, a farmer is more likely to adopt a technology if its operation is perceived to align with their existing agronomic practices.

The belief structure within the Decomposed Theory of Planned Behaviour is flexible and can be modified to suit different research objectives (Shao et al., 2022). An additional variable (risk) is introduced from Expected Utility Theory. Expected Utility Theory assumes that an individual's adoption behaviour is predicted by perceived risk associated with the new technology, uncertainty about the outcomes of using it, and the superior value expected from new technology adoption, in relation to whether it surpasses that of an older or existing technology (Mongin & Baccelli, 2021). This implies that a farmer compares a new technology with an existing technology or practice and is more likely to adopt the new technology if it guarantees a higher expected utility (Borges et al., 2015; Meijer et al., 2015; Schoemaker, 1982). Expected Utility (von Neumann & Morgenstern, 1953) was added to the model. It was assumed that a farmer would adopt renewable energy technology if its application is perceived to result in greater Expected Utility.

Given these assumptions, the following hypotheses have been formulated.

- H4: Greater Perceived Ease of Use will positively affect attitude to adopt renewable energy technology for farming.
- H5: Greater Perceived Usefulness will positively affect attitude toward adopting renewable energy technology for farming.
- H6: Greater perceived compatibility will positively affect attitude to adopting renewable energy technology for farming.
- H7: Lower Perceived Risk will positively affect a farmer's attitude to adopt renewable energy technology for farming.

According to Fishbein and Ajzen (1977), Subjective Norms are the social pressures that affect an individual's intention to engage in a behaviour. Subjective Norms can be deconstructed into two sub-constructs: "Peer Influence" and "External Influence". In Ghana, farmers live in communities comprised of both family and non-family members (e.g. spouses, children, and colleague farmers etc.) and are involved in various social interactions (Awuni et al., 2018). Here, Peer influence is assumed to occur when colleagues or family members within their immediate community persuade a farmer to decide whether to adopt a renewable energy technology. External influence occurs when a farmer is convinced by people outside their immediate community such as researchers, agricultural extension professionals and other non-farmer stakeholders to adopt new technology. The following hypotheses have been formulated.

- H8: Perceived peer influence (whether positive or negative) will (positively and negatively) affect subjective norm to adopt renewable energy technology for farming.

- H9: Perceived external influence (whether positive or negative) will (positively and negatively) affect subjective norm to adopt renewable energy technology for farming.

In the Decomposed Theory of Planned Behaviour, Perceived Behavioural Control is comprised of three underlying sub-constructs: Self-efficacy, Resource-Facilitating Conditions, and Technology-Facilitating Conditions. Here, Self-Efficacy refers to the ability of an individual to perform an action. For example, a farmer will adopt a new technology that is perceived to be operational without physical or psychological discomfort. Positively perceived resource and technology-facilitating conditions stimulate an intention to adopt a renewable energy technology. For farmers, resource-facilitating conditions may include perceptions that they have sufficient time, access to capital, and appropriate agronomic conditions to adopt a particular technology. Technology facilitating conditions may include the perceived availability of spare parts for equipment, access to markets, and specialist support in relation to repair equipment and machinery repair (Nyasulu & Dominic Chawinga, 2019; Taylor & Todd, 1995a). The following hypotheses are proposed.

- H10: Higher perceived self-efficacy will increase perceived behavioural control to adopt renewable energy technology for farming.
- H11: Greater perceived access to resource-facilitating conditions will increase perceived behavioural control to adopt renewable energy technology for farming.
- H12: Greater perceived access to technology-facilitating conditions will increase perceived behavioural control to adopt renewable energy technology for farming.

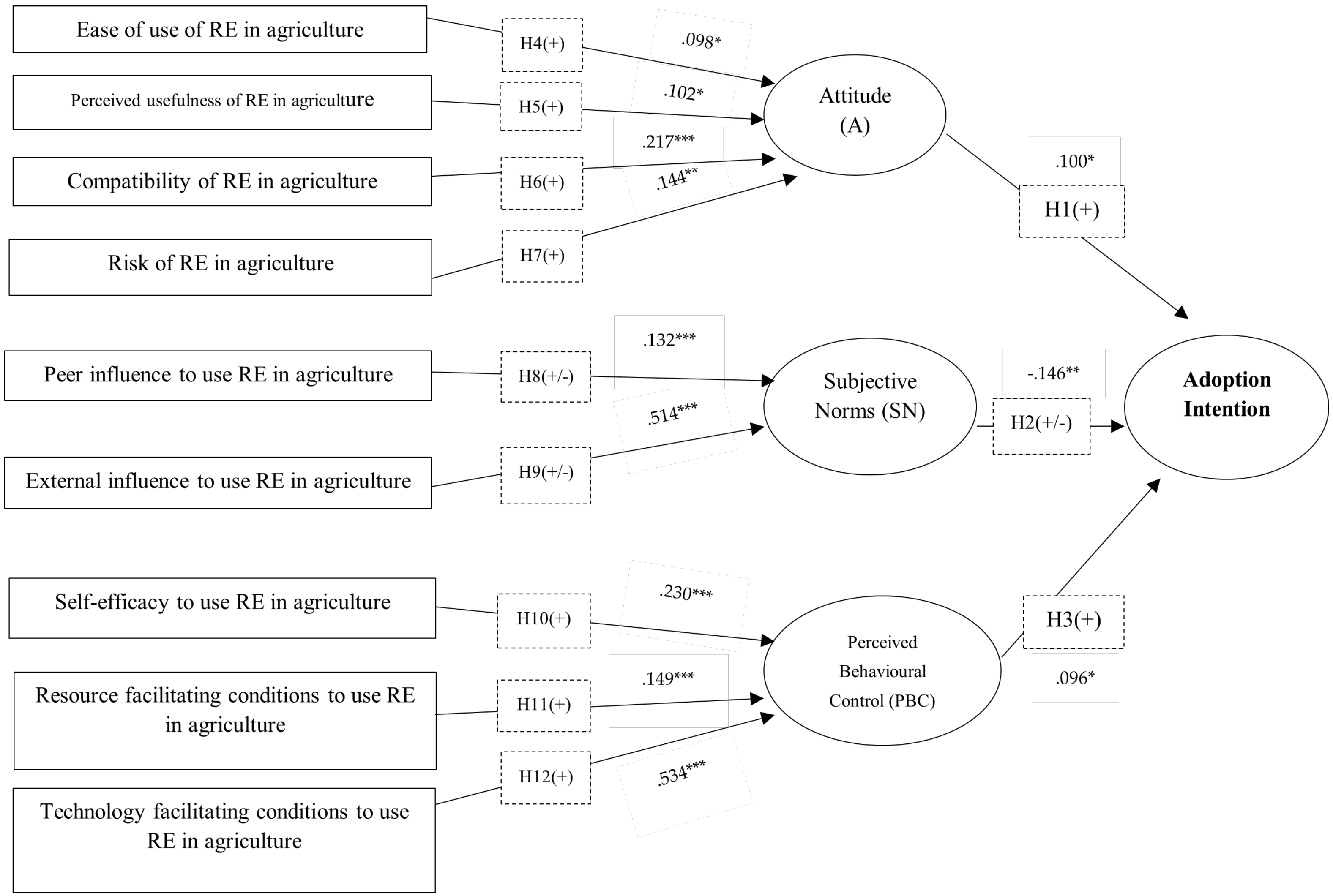

Figure 1. Constructs predicting farmers' behavioural intentions to adopt renewable energy technology (adapted from the Decomposed Theory of Planned Behaviour). The direction of the hypothetical relationship is indicated in brackets for each Hypothesis. (RE = Renewable Energy) Adapted and modified from Taylor and Todd (1995a).

3. Materials and Methods

3.1. Data Collection

A survey was designed to collect data (May 2023) from farmers in the Upper West Region of Northern Ghana where agriculture is the main source of livelihood. The survey used a 5-point Likert scale (i.e., strongly disagree to strongly agree) to measure variables, including constructs contributing to Attitude factors (Perceived Usefulness, Perceived Ease of Use, Perceived Compatibility, and Perceived Risk), Subjective Norms (Perceived Peer and External Influences), and Perceived Behavioural Control (Perceived Self-Efficacy, Perceived Technology Facilitating Conditions, and Resource Facilitating Conditions). The survey was developed in English, and an online version was created using the KobToolbox application. Ethical approval was obtained from the Faculty of Science, Agriculture and Engineering prior to data collection, Newcastle University (Ref: 32218/2023; 11/05/2023).

The survey had five sections: 1) General/background information, 2) Energy use in agriculture, 3) Socioeconomic drivers and barriers, 4) Psychological drivers and barriers, and 5) External drivers facilitating sustainable energy adoption. Yamene's formula (Bala & El-jajah, 2019) was used to determine the sample size indicating that a total of 429 farmer interviews were required. A systematic sampling technique was used to select farmers to participate in the survey. The participant sample was selected from the overall farmer population within the sampling area at regular intervals (Singh & Singh, 1977). Farmers were identified through household sampling. Following the initial random selection of a household within the sampling frame, subsequent households were selected after every 10th interval count of households. The systematic sampling technique was used due to its simplicity in terms of application, and robustness in relation to obtaining representativeness within a population (Castillo, 2009; Elsayir, 2014; Opsomer et al., 2012). The head of a selected household was the first point of contact and was asked for permission prior to an interview being conducted with a participant farmer. This is in line with the traditional entry protocol when visiting households in the study area. Farmer participants were targeted through households because 80 percent of households in the research area engaged in farming. One farmer was interviewed per household. Therefore, household heads (predominantly represented by male farmers) dominated the participants sampled).

3.2. Research Area

Lawra Municipality was selected for the research. Agriculture is the major economic activity in this municipality, with about 80 percent of the working population being employed in agriculture-related work (Lawra Municipal Assembly, 2018). Agriculture in this area is predominantly undertaken within smallholdings, mainly to provide food for household consumption. Crops cultivated include maize, millet, groundnuts, soya bean and cowpea. In addition, livestock farming includes goats, pigs, sheep, poultry, and cattle. Depleted soil fertility, erratic rainfall patterns, the occurrence of agricultural pests and diseases, farmers' limited access to credit, and inadequate access to technology, extension services, and markets threaten farmers only source of livelihood and food security (Lawra Municipal Assembly, 2018).

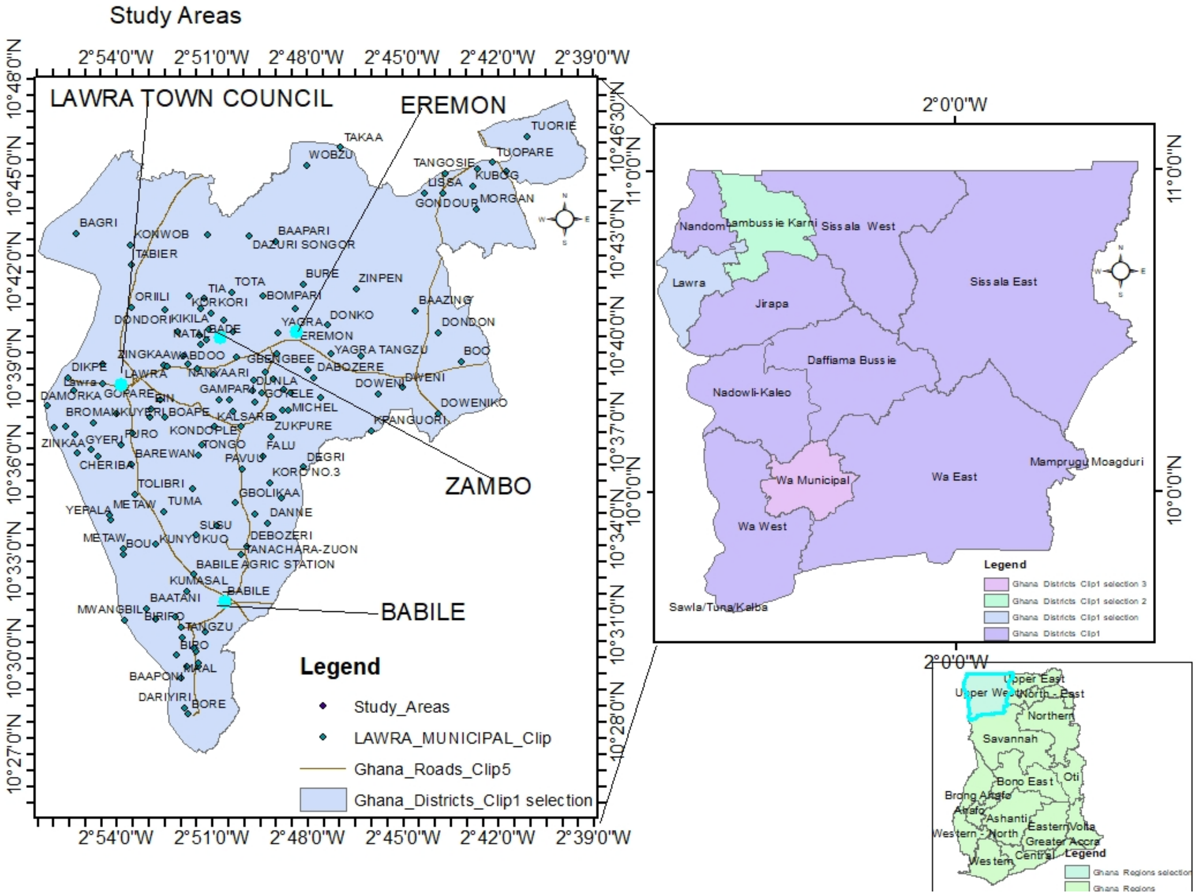

Figure 2. Map of the research area.
Source: Author's own (2023).

3.3. Data Analysis

A total of 429 farmer survey interviews were conducted. Following the exclusion of incomplete surveys, 418 completed responses were obtained and subsequently included in the analysis. A descriptive analysis of the demographic and background attributes of the farmers was analysed using SPSS version 29. Structural Equation Modelling (SEM) was conducted using AMOS 29 to test the research hypotheses (https://www.ibm.com/support/pages/downloading-ibm-spss-amos-29-0). SEM was applied to assess the relationship between variables or constructs in the adapted research model (Savalei & Bentler, 2006; Ullman & Bentler, 2012), allowing the assessment of complex and multiple relationships underpinning numerous variables, and testing the predictivity of theoretical models using empirical data (Bollen & Noble, 2011; Chin, 1998).

Confirmatory factor analysis was initially applied to assess the validity of the constructs included in the research model (Hoyle, 2000; Stapleton, 1997; Stevens, 1996). Confirmatory factor analysis as opposed to Exploratory factor analysis was applied because the underlying factors contributing to constructs used in the model had been identified and validated in previous research (Bagheri et al., 2016; Fishbein & Ajzen, 1977; Musyoki et al., 2022; Rezaei et al., 2020; Sharifzadeh et al., 2017; Venkatesh et al., 2003).

3.4. Definition of Measurement Scales

A total of 45 items were included in the measurement scales used to measure the constructs. Each construct consisted of at least three items in the form of a statement and scored using a Likert scale from 1 to 5 (where 1 = strongly disagree, 2 = disagree, 3 = neither agree nor disagree, 4 = agree, and 5 = strongly agree). Table 2 summarises items and constructs measured in the research.

Table 2. Items used to measure constructs in the research.

Constructs	Item	Sources
Perceived Ease of Use	EU1 (It will be stress-free for me to use solar technology for farming). EU2 (I will be comfortable operating solar technology alone). EU3 (It will be stress-free for me to use biomass technology for farming).	Bagheri et al., 2016; Davis, 1989; Rezaei et al., 2020
Perceived Usefulness	PU1 (Using solar technology will increase my yields). PU2 (Using solar technology will increase my profits). PU3 (Using biomass technology will increase my yields). PU4 (Using biomass technology will increase my profits).	Davis, 1989; Rezaei et al., 2020
Perceived Compatible	CT1 (Adopting solar technology suites the type of farming I practice). CT2 (Adopting solar technology is compatible with indigenous farming practices). CT3 (Adopting biomass technology suites the type of farming I practice).	Rogers, 2003; Sharifzadeh et al., 2017
Perceived Risk	RK1 (Using solar technology has no effect on my farm income). RK2 (Using biomass technology has minimal or no effect on my farm yields). RK3 (Using biomass technology has no effect on my farm income).	Musyoki et al., 2022
Perceived Peer Influence	PI1 (A family member will approve the use of solar technology for farming). PI2 (A neighbour will approve the use of solar technology for farming). PI3 (A family member will approve the use of biomass technology for farming). PI4 (A neighbour will approve the use of biomass technology for farming).	Taylor & Todd, 1995b
Perceived External Influence	EI1 (An agricultural extension officer will approve the use of solar technology for farming). EI2 (Members of a farmer cooperative/association will approve the use of solar technology for farming). EI3 (An agricultural extension officer will approve the use of biomass technology for farming). EI4 (Members of a farmer cooperative/association will approve the use of biomass technology for farming).	Taylor & Todd, 1995b
Perceived Self-efficacy	SE1 (I think I have the personal ability required to use solar technology for farming). SE2 (I think I understand how solar technology for farming works. SE3 (I think I have the personal ability required to use biomass technology for farming). SE4 (I think I understand how biomass technology for farming works).	Ajzen, 1991; Sharifzadeh et al., 2017
Resource Facilitating Conditions	RFC1 Using solar energy will require ownership of plot(s) of land(s). RFC2 Using solar energy will require adequate money/funds. RFC3 (Using biomass energy will require crop/livestock residue) RFC4 (Using biomass energy will require money/funds).	Venkatesh et al., 2003
Technology Facilitating Conditions	TFC1 (To use solar technology, the spare parts to mend the equipment must be available). TFC2 (To use solar technology, technical experts/equipment repairers must be available). TFC3 (To use biomass technology, the spare parts to mend the equipment must be available). TFC4 (To use biomass technology, technical experts/equipment repairers must be available).	Venkatesh et al., 2003
Attitude	ATT1 (Solar technology is affordable compared to other energy technologies). ATT2 (Biomass technology is useful to me for farming). ATT3 (I will be comfortable operating solar technology alone). ATT4 (Using solar technology has minimal or no effect on my farm yields).	Ajzen, 1991; Fishbein & Ajzen, 1977
Subjective norm	SN1 (Other farmers similar to myself will approve the use of solar technology for farming). SN2 (Other farmers similar to myself will approve the use of biomass technology for farming). SN3 (Leaders of a farmer Cooperative/Association will approve the use of biomass technology for farming).	Ajzen, 1991; Fishbein & Ajzen, 1977

Table 2. *Cont.*

Perceived behavioural control	PBC1 (To use solar technology, it must be available in the market for adoption). PBC2 (Biomass energy has a relatively lower cost.) PBC3 (To use biomass technology, it must be available in the market for adoption).	Ajzen, 1991; Fishbein & Ajzen, 1977
Adoption Intention	AI1 (What is the likelihood that you will adopt solar energy for agriculture?) AI2 (What is the likelihood that you will adopt biomass energy for agriculture?)	Taylor & Todd, 1995b

4. Results

4.1. Socio-demographics

Most participants were male (79%) and had no formal education (64%), with only (22%) obtaining primary school education (Table 3). Although females represented the majority of the population in Lawra Municipality, male farmers formed the majority of the survey participants primarily because they represented household heads and owned the land on which farming was conducted. This reflects the culture of the Lawra traditional area and the larger Ghanaian society where inheritance is predominantly patrilinear such that males are more likely to inherit, or own land compared to females (Bonye, 2022; Vanderpuye et al., 2020). These existing socio-cultural practices have biased the participatory process, resulting in men dominating the research participants included.

Table 3. Summary of descriptive statistics of farmers' socio-demographic characteristics.

VARIABLES	MEAN	SD	
Age (years)	48.03	9.98	
Household size (number of people)	6.96	3.42	
Farm size (acres)	5.22	2.16	
Farmer experience (years)	16.85	10.20	
Farmer income (GHS-Ghana Cedis)	764.52	597.59	
Energy cost (GHS)	239.33	158.25	
VARIABLES	**CATEGORIES**	**FREQUENCY**	**PERCENTAGE (%)**
Gender	Male	329	78.7
	Female	89	21.3
Education	None	267	63.9
	To Primary school	91	21.8
	To Junior high school	42	10.0
	To Senior high school	12	2.9
	To Tertiary	6	1.4
Purpose of farming	Food/household consumption	410	98.1
	Income	5	1.2
	Traditional heritage	3	.7
Farm labour source	Extended family	131	31.3
	Hired labour	116	27.8
	Household	171	40.9

The average age of farmers was 48 years, and average farming experience was 17 years. On average, a farmer's household was comprised of 7 members with an average farm size of 5 acres (about 2 hectares). Household members contributed an average of 41% to farm labour. Other sources of farm labour included extended family members (31%) and hired labour (28%). Annually, the average cost of farm energy inputs was about GHS239.00 (USD19.14). The annual farm income of farmers was about GHS765.00 (USD61.26). About 98% of farmers primarily cultivated land to provide food for household consumption.

4.2. Constructs Reliability and Validity Analysis

A construct reliability analysis was performed to estimate the internal consistency of the items included in each construct. A composite reliability (CR) test was performed, where all the research constructs had values ranging from 0.807 to 0.978, which was greater than the acceptable value of 0.7 or higher (see Table 4; Anderson & Gerbing, 1988; Chen, 2016). Convergent and discriminant validity analyses were conducted (Chen, 2016; Hair et al., 2021). Using the average variance extracted (AVE), convergent validity was established, with all constructs reaching the acceptable value of > 0.5 (Fornell & Larcker, 1981; Naqshbandi et al., 2015). Discriminant validity was measured using the Fornell and Larcker (1981) principle, where the square root of AVE needs to be greater than the correspondence of an individual construct against other constructs (Hair et al., 1998; Kline, 2023). The results suggested discriminant validity was acceptable (Table 5).

Table 4. Reliability and Convergent Validity of Constructs.

Constructs	CR > 0.7	AVE > 0.5	MSV	ASV	Convergent Validity CR>AVE AVE>.5
Perceived Behavioural Control	0.927	0.810	0.420	0.186	YES
Perceived Ease of Use	0.931	0.820	0.235	0.025	YES
Perceived Usefulness	0.807	0.521	0.342	0.118	YES
Compatibility	0.867	0.623	0.334	0.082	YES
Risk	0.876	0.703	0.129	0.039	YES
Peer Influence	0.870	0.634	0.420	0.174	YES
External Influence	0.855	0.613	0.397	0.168	YES
Self-Efficacy	0.883	0.656	0.159	0.059	YES
Resource Facilitating Conditions	0.868	0.569	0.090	0.025	YES
Technology Facilitating Conditions	0.901	0.703	0.377	0.135	YES
Attitude	0.897	0.686	0.104	0.035	YES
Subjective Norms	0.886	0.722	0.335	0.109	YES
Adoption Intention	0.978	0.956	0.235	0.031	YES

Note: CR = Composite Reliability; AVE = Average Variance Extracted; MSV = Maximum Shared Squared Variance; ASV = Average Shared Squared Variance.

Table 5. Discriminant Validity Analysis of Constructs.

Perceived Behavioural Control	Ease Of Use	Perceived Usefulness	Compatibility	Risk	Peer Influence	External Influence	Self-Efficacy	Resource Facilitating Conditions	Technology Facilitating Conditions	Attitude	Subjective Norms	Adoption Intention	Discriminant Validity MSV<AVE ASV<AVE
0.900													YES
−0.064	**0.905**												YES
0.524	−0.027	**0.722**											YES
0.578	0.011	0.257	**0.790**										YES
0.204	0.031	0.233	−0.008	**0.838**									YES
0.648	−0.063	0.487	0.364	0.293	**0.796**								YES
0.611	−0.115	0.417	0.392	0.359	0.630	**0.783**							YES
0.287	−0.109	0.323	0.204	−0.040	0.399	0.345	**0.810**						YES
0.196	−0.139	0.074	0.179	0.077	0.135	0.238	0.078	**0.754**					YES
0.614	−0.014	0.585	0.306	0.241	0.584	0.439	0.177	0.127	**0.839**				YES
0.323	0.098	0.173	0.214	0.165	0.267	0.245	0.100	0.052	0.190	**0.828**			YES
0.421	−0.058	0.342	0.231	0.177	0.476	0.579	0.370	0.300	0.352	0.062	**0.850**		YES
0.077	0.485	−0.118	0.168	−0.169	−0.002	−0.113	−0.088	−0.084	−0.071	0.124	−0.100	**0.978**	YES

Note: Values in bold are the square roots of AVEs of relevant constructs in Table 4.

4.3. Measurement Model Evaluation

Structural Equation Modelling involving a two-step approach was conducted to test the research model. The maximum-likelihood approach was used to estimate the parameters of the model (measurement model evaluation; Hair et al., 1998). The evaluation of the goodness-of-fit indices to validate the research model against the data was conducted.

Three fit indices are needed to establish an acceptable model fit (Hair et al., 2003; Holmes-Smith et al., 2006; Zhou & Abdullah, 2017). To establish and report on an overall goodness-fit model, the absolute fit indices and comparative fit indices were used to evaluate the fitness of the research model. According to Byrne (2013), CMIN/DF, RMSEA, CFI, IFI, and TLI are sufficient to establish the overall goodness-fit model.

The initial measurement model evaluation generated the following indices CMIN/DF = 3.073, RMSEA = 0.71, CFI = .869, TLI = .852, and IFI = .870. (CMIN/DF and RMSEA) which met the recommended values (CFI, TLI, and IFI) but did not satisfy the goodness-of-fit criteria; hence, an overall model fit was not obtained. The model fit was improved by deleting items and correlating error terms as specified under the model's modification indices (MIs). According to Anderson and Gerbing (1988) and Lassoued (2014), connecting or deleting indicators can improve an unacceptable model fit. Improving a poor model fit (i.e., model re-specification) is required in SEM when the goodness-of-fit model indicators do not meet the acceptable threshold (Anderson & Gerbing, 1988; Bagozzi & Yi, 2012; Saris et al., 1987). As a result, the following items (PU3, CT1, PI1, PI4, EI1, SE1, SE2, RFC1, RFC4, and TFC1) were deleted from the model with the model modification indices of (>30). Consequently, an adequate and acceptable overall model fit was established CMIN/DF = 2.573, RMSEA = 0.61, CFI = 0.932, TLI = 0.918, and IFI = 0.933.

4.4. Structural Model Evaluation (Hypotheses Testing)

Given that the measurement model was evaluated, modified and yielded an overall good model fit, the structural model was evaluated, and the research hypotheses tested. From the hypothetical model, it is assumed that positive Attitude, positive Perceived Subjective Norms, and high Perceived Behavioural Control directly predict a farmer's Behavioural Intention to adopt renewable energy technology. It is further assumed that greater Perceived Ease of Use, greater Perceived Usefulness, greater Compatibility, higher Perceived Risk, higher Perceived Peer and External influence, higher Self-Efficacy, and greater Perceived Access to Resources and Technology Facilitating Conditions affect Attitude, Subjective Norms, and Perceived Behavioural Conditions. The goodness-of-fit indices were re-evaluated to ensure the model fit the data being used for the structural model evaluation and testing of the hypothesised relationships in the model. Overall, the goodness-of-fit indices reported satisfied the recommended values: CMIN/DF = 3.060, RMSEA = 0.70, CFI = 0.906, TLI = 0.900, and IFI = 0.907.

The results of the structural modelling showed that all the hypothesised relationships in the model were supported with the exception of Subjective Norms (see Table 6).

Table 6. Results of hypotheses testing.

Hypothesis	Regression Path	Coefficients (SRW)	P-value	Remarks
H1: A positive attitude will positively affect a farmer's intention to adopt a renewable energy technology for farming.	Attitude ---> Adoption Intention	.100	.055*	Supported
H2: Positive perceived subjective norms will positively affect a farmer's intention to adopt a renewable energy technology for farming.	Subjective Norms --->Adoption Intention	−.146	.007**	Not supported
H3: High perceived Behavioural Control will positively affect a farmer's intention to adopt a renewable energy technology for farming.	Perceived Behavioural Control ---> Adoption Intention	.096	.072*	Supported
H4: Greater perceived ease of use will positively affect a farmer's attitude to adopt renewable energy technology for farming.	Perceived ease of use ---> Attitude	.098	.056*	Supported
H5: Greater perceived usefulness will positively affect a farmer's attitude to adopt renewable energy technology for farming.	Perceived usefulness ---> Attitude	.102	.092*	Supported
H6: Greater perceived compatibility will positively affect a farmer's attitude to adopting renewable energy technology for farming.	Compatibility ---> Attitude	.217	0.01***	Supported
H7: Lower perceived risk will positively affect a farmer's attitude to adopt renewable energy technology for farming.	Risk ---> Attitude	.144	.008**	Supported
H8: Peer influence will affect a farmer's subjective norm to adopt renewable energy technology for farming.	Peer influence ---> Subjective Norms	.132	.013**	Supported
H9: External influence will affect a farmer's subjective norm to adopt renewable energy technology for farming.	External influence ---> Subjective Norms	.514	0.01***	Supported
H10: Higher perceived self-efficacy will positively affect a farmer's perceived behavioural control to adopt renewable energy technology for farming.	Self-efficacy ---> Perceived Behavioural Control	.230	0.01***	Supported
H11: Greater perceived access to resource-facilitating conditions will positively affect a farmer's perceived behavioural control to adopt renewable energy technology for farming.	Resource facilitating conditions ---> Perceived Behavioural Control	.149	0.01***	Supported
H12: Greater perceived access to technology-facilitating conditions will positively affect a farmer's perceived behavioural control to adopt renewable energy technology for farming.	Technology facilitating conditions ---> Perceived Behavioural Control	.534	0.01***	Supported

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$ indicate statistical significance at 1%, 5%, and 10% respectively.
*Standardised Regression Weight – SRW

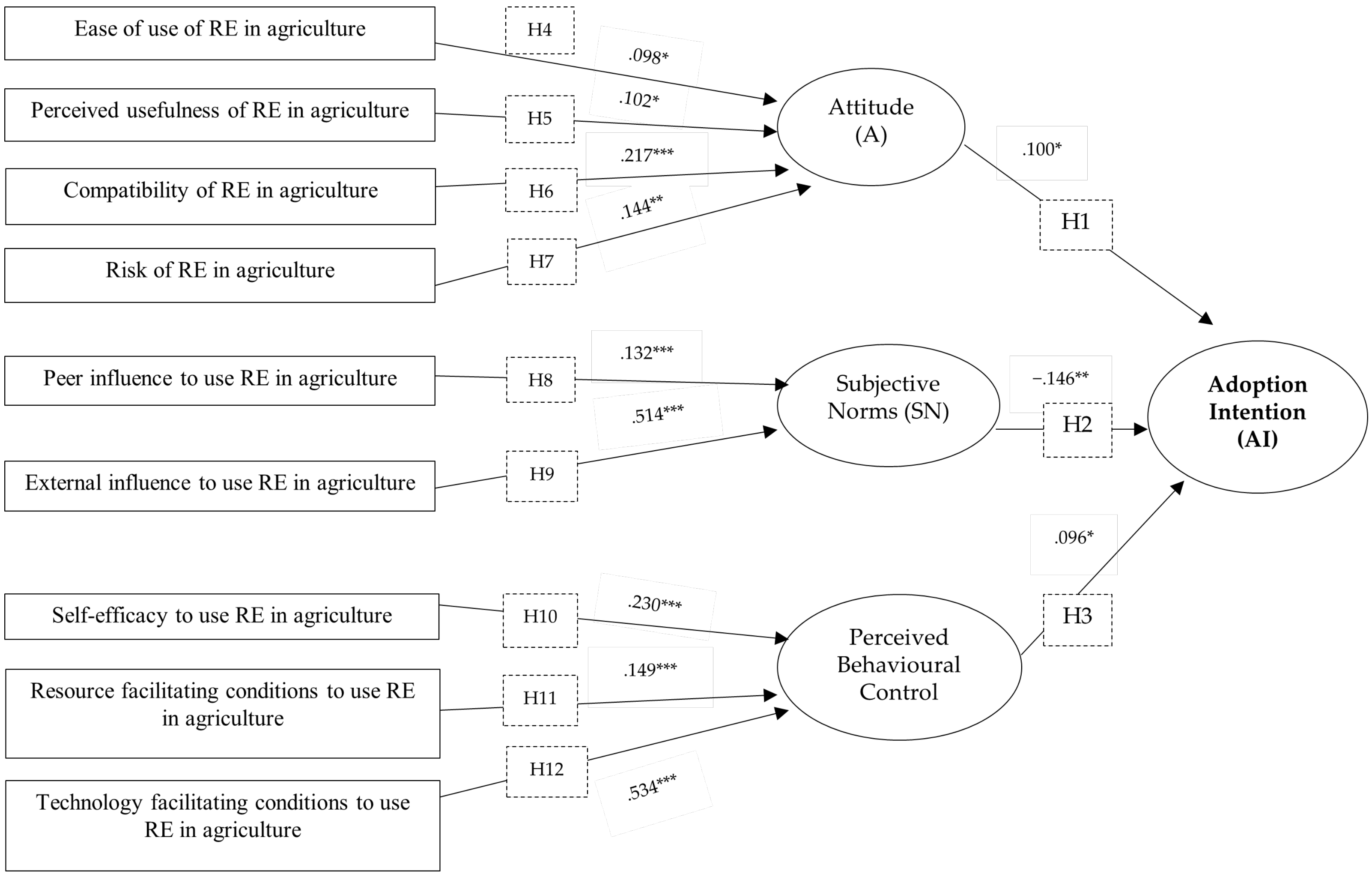

Figure 3. Results of structural regression path of the hypothesised model (DTPB).
Note: *** p < 0.01, ** p < 0.05, * p < 0.10 indicate statistical significance at 1%, 5%, and 10% respectively.

5. Discussion

The results showed that positive Attitude and high Perceived Behavioural Control positively and moderately affected farmers' intention to adopt renewable energy technology in their agronomic practices. Similarly, farmers perceived that if they had greater access to conditions for renewable energy technology, they were more likely to develop an intention to adopt renewable energy. These results are consistent with earlier research, which found that farmers' intention to adopt new technology was significantly influenced by a positive attitude towards the technology and perceived control over adoption (Bagheri et al., 2019; Borges et al., 2014; Bruijnis et al., 2013; Lalani et al., 2016; Rezaei et al., 2020; Tama et al., 2021; Yazdanpanah et al., 2014). At present, the use of renewable energy technology in farming is not widespread in Lawra Municipality (Karbo et al., 2022; Stock et al., 2023). However, these results suggest that if farmers have a positive attitude towards renewable energy technology, they are more likely to develop an intention to adopt it. Therefore, developing interventions that change farmers' attitudes to be more positive will increase the likelihood of them adopting renewable energy. This might be achieved, for example, through introducing renewable energy technology to farmers using learning platforms, including field demonstrations and trials to demonstrate the benefits of using the technology (Cheung & Vogel, 2013; Gebrezgabher et al., 2015; Rezaei et al., 2020; Zeweld et al., 2017a).

Subjective Norms did not positively influence farmers' intention to adopt renewable energy technology but rather had a negative relationship with behavioural intention. Similar research findings by (Bagheri et al., 2019; Elahi et al., 2022; Maleksaeidi & Keshavarz, 2019; Tama et al., 2021) found a negative relationship between subjective norms and farmers' behavioural intention to adopt agricultural technologies. Further, this finding is consistent with previous research that reported that perceived subjective norms did not positively influence individuals' adoption intention due to social factors such as cultural differences and perceived bias in relation to technology (Bagheri et al., 2021; Buyinza et al., 2020; Laksono et al., 2022; Tan et al., 2017). It is also possible that few farmers in the study area were adopting renewable energy technology for farming when the research was conducted, creating a normative social environment in relation to the non-adoption of renewable energy, and so had a negative association with behavioural intention. If in the future it is the case that where more farmers adopt renewable energy for farming, peer-to-peer learning may be leveraged leading to a normative social environment that will positively affect farmers' behavioural intention to adopt renewable energy technology (Devi et al., 2020; Nyambo et al., 2022).

As predicted by the model, greater Perceived Compatibility and lower Perceived Risk had significant positive effects on farmers' attitudes to adopt renewable energy technology. The results are consistent with those of Dixit et al. (2023) and Rezaei et al. (2020), which suggested that farmers adopt innovative technologies compatible with their contextual and pragmatic situations. For example, farmers in Lawra Municipality are more likely to adopt renewable energy technologies (e.g., solar energy to power water pumps to irrigate crops). In Lawra Municipality, farmers are economically dependent primarily on agriculture. As a consequence, they are less likely to adopt technologies which pose a risk to their only source of income, and which potentially have minimal or no risk to their agricultural productivity. Greater Perceived Ease of Use and greater Perceived Usefulness had positive but moderate effects on farmers' attitudes to adopt renewable energy technology. Farmers' perceptions of the ease of use and usefulness of renewable energy technologies may depend on farmers' level of experience or information they have acquired about the technology. Therefore, when farmers obtain sufficient information about how to use a renewable energy technology, and the extent to which it is useful, they will indicate greater intentions to adopt it. Perceived Ease of Use and Usefulness has also been shown to positively influence farmers' adoption behaviour of agricultural innovations (Dixit et al., 2023; Kardooni et al., 2016; Li et al., 2021; Ulhaq et al., 2022).

A positive effect of peer and external influences on farmers' subjective norms associated with adopting renewable energy technology was observed. Adesina and Chianu (2002); Li et al. (2020); Wang et al. (2019) reported that peer and external influences affected farmers' adoption of agricultural innovations (the construct of subjective norms). As agricultural extension agents are influential in relation to developing a Subjective Norm which favours adoption, the government could ensure sufficient resources are allocated to agricultural extension activities focused on promoting the adoption of renewable energy technology and other innovations which will help the agriculture sector attain Net Zero targets. This in turn will positively influence behavioural intention. Peer Influence also influences Subjective Norms. The former is likely to become more positive as more farmers adopt renewable energy and this Subjective Norm would be indirectly influenced by extension service and other knowledge exchange activities associated with the promotion of renewable energy in agriculture which in turn would influence behavioural intention.

Positive effects of perceived high Self-Efficacy, greater perceived Access to Resource Facilitating Conditions, and greater perceived Access to Technology Facilitating Conditions were observed in relation to the Perceived Behavioural Control of farmers to adopt renewable energy.

Yazdanpanah et al. (2022) reported that greater perceived Self-Efficacy increased farmers' intention to adopt new technologies. Higher perceived Self-Efficacy implies that farmers perceive themselves as having a greater ability to adopt renewable energy technology without at the same time perceiving difficulty in doing this. Therefore, higher perceived Self-Efficacy on the part of farmers should lead to a greater perception of Perceived Behavioural Control over their adoption of renewable energy technology for farming. In addition, farmers are more likely to develop an intention to adopt renewable energy technology when they believe resources such as land and financial support are readily accessible. Again, extension workers may be instrumental in identifying training requirements to provide the knowledge required to adopt renewable energy which addresses the issue of perceived Self-Efficacy, especially if this is coupled with policies which promote (e.g. infrastructure requirements, subsidy programmes and technology support) in relation to renewable technology adoption. For example, there is evidence that the adoption of renewable energy by farmers is contingent on the technology and spare parts being both available and accessible to end-users. For example, Faridi et al. (2020) and Oliveira et al. (2014) reported that perceptions of facilitating conditions determined farmers' behavioural intention to adopt new technologies.

5.1. Theoretical and Practical Implications

This research extends the application of the Decomposed Theory of Planned Behaviour to predict farmers' adoption behaviour in relation to renewable energy technology in Northern Ghana, within an LMIC country demonstrating that the Decomposed Theory of Planned Behaviour can potentially be used in future research can be applied to predict and explain farmers' technology adoption behaviours.

The Decomposed Theory of Planned Behaviour integrates constructs from the Technology Acceptance Model, the Theory of Planned Behaviour, and the Diffusion of Innovation Theory (Taylor & Todd, 1995a). In this research, a perceived risk variable from Expected Utility Theory was added to the model. Perception of lower risk was a significant predictor of farmers' adoption behaviour. Future research may need to consider a wide range of variables or factors that can be integrated into the Decomposed Theory of Planned Behaviour to explain farmers' adoption behaviour.

The Decomposed Theory of Planned Behaviour assumes that Subjective Norm influences an adoption behaviour, which could be positive or negative. While Subjective Norms have also been reported to increase the adoption intention of farmers (Elahi et al., 2022; Maleksaeidi & Keshavarz, 2019; Tama et al., 2021), these results suggest an understanding of the social environment in which social pressures are generated that potentially affect farmers' adoption behaviour is needed, including within the context of the Decomposed Theory of Planned Behaviour in relation to understanding farmers' adoption behaviour.

5.2. Limitations

A major limitation of this research was its focus on investigating farmers' intention to adopt renewable energy technology rather than the adoption behaviour itself. At the time of conducting the research, renewable energy technology for farming was not widespread in Ghana with solar and biomass energy technology being the most likely adopted renewable energy forms by farmers. Future research might investigate how behavioural intention relates to the technology's actual adoption. Various forms of renewable energy, including solar, biomass, hydro, and wind-based technologies, can support agricultural activities. This research limited the focus of renewable energy technology to solar and biomass technologies because these prominent forms of renewable energy are being promoted to Ghanaian farmers for application within the agricultural sector.

A second, and important, limitation was the sampling approach, which was skewed towards the inclusion of more male participants. While females constitute the majority of the population in Lawra Municipality, male farmers (79%) formed the majority of the survey participants primarily because they represented household heads and owned the land on which farming was conducted. However, the results may exclude the perspective of women in the context of farming and renewable energy adoption in Northern Ghana. Future research may expand the inclusion criteria for participants beyond the household to capture more female farmers who often are not household heads and do not own farmlands but contribute significantly to performing farm activities.

5.3. Recommendations

Policymakers could consider farmers' psychological characteristics when formulating policies and interventions to promote the adoption of renewable energy technology. Such policies and interventions that align with farmers' psychological attributes can enhance farmers' perception of renewable energy technology and consequently increase the likelihood of their adopting it.

Agricultural policy development should not be informed only by economic factors but must also address psychological factors determining adoption.

Policies to provide achievable targets and clear roadmaps in relation to developing and facilitating the adoption of renewable energy technology by farmers and other actors in the agricultural value chain are needed. This implies that governments could establish pragmatic policy regimes, including tax and credit subsidies and green financing frameworks to increase support for farmers to adopt renewable energy technology (Balana & Oyeyemi, 2020; Taghizadeh-Hesary & Yoshino, 2020). Technology innovators and designers should consider farmers' psychological factors when developing renewable energy technology potentially resulting in the development of wide-ranging renewable energy technology to align the farming needs of different farmers.

6. Conclusions

Renewable energy can contribute to reducing carbon emissions and achieving more sustainable agriculture practices. To increase adoption in agriculture, factors determining farmers' adoption need to be understood. In line with this, a theoretical model was applied in this research to understand predictors of farmers' adoption of renewable energy technology for farming. The Decomposed Theory of Planned Behaviour predicts behavioural intention based on three main psychological constructs, Attitude, Subjective Norms, and Perceived Behavioural Control, which are affected by sub-constructs. From the model, it was concluded that farmers' behavioural intention to adopt renewable energy was influenced by Attitude and high Perceived Behavioural Control. In addition, farmers' Attitude towards renewable energy adoption was affected by greater perceived Ease of Use, greater Perceived Usefulness, higher Perceived Risk, and greater Perceived Compatibility. Although farmers' Subjective Norms did not positively influence behavioural intention to adopt renewable energy, farmers' subjective norms towards renewable energy were affected by Peer and External Influences. Further, farmers Perceived Behavioural Control towards renewable energy adoption was determined by high perceived Self-Efficacy, greater perceived Access to Resource Facilitating Conditions, and Technology Facilitating Conditions. The findings of the research contribute to our understanding of farmers' intention to adopt renewable energy for farming, as well as providing evidence for policy and extension activities which may promote the adoption of renewable energy in Ghanaian agriculture.

CRediT Author Statement: Ransford Teng-viel Karbo: Conceptualisation, Methodology, Data collection, Data curation, Formal analysis, Writing – original draft, and Writing – review and editing; **Lynn J. Frewer:** Conceptualisation, Methodology, Supervision, and Writing – review and editing; **Francisco J. Areal:** Conceptualisation, Methodology, Supervision, and Writing – review and editing; **Albert Boaitey:** Conceptualisation, Methodology, Supervision, and Writing – review and editing; **Glyn Jones:** Conceptualisation, Methodology, Supervision, and Writing – review and editing; **Guy Garrod:** Writing – review and editing.

Data Availability Statement: Data will be made available on request.

Funding: This research was funded by the Ghana Education Trust Fund (GETFUND).

Conflicts of Interest: The authors declare no conflict of interest.

Acknowledgement: Not applicable.

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