



Rural small scale farmers' smart mobile phone usage acceptance prognosticators for agricultural marketing information access

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Abstract

The purpose of the article is to examine the rural small scale farmers' smart mobile phone usage acceptance prognosticators for agricultural marketing information access in selected farming towns in Zimbabwe. Responses were collected from rural small scale farmers in Marondera, farming town in Zimbabwe using structured questionnaire with a 7 point Likert scale. The research study depicted that trust, social influence, perceived risk and relative advantage have positive influence on rural small scale farmers' smart mobile phone usage acceptance for agricultural marketing information access adoption intention in Zimbabwe. The study has limitations which may affect the generalisability of the results since they can only be applied to the studied areas, all in Mashonaland East province of Zimbabwe. Agricultural marketers are encouraged to focus more attentively on smart mobile phone acceptance determinants such as social influence, perceived risk and trust when devising mobile agricultural marketing strategies especially during uncertain times. The study adds to theoretical literature development by extending knowledge on the UTAUT2 theoretical framework since there is paucity of research that have directly applied the same model in agricultural marketing and general agribusiness. Practically, the study enhances the need for adoption of contemporary technologies to solve the current challenges facing farmers in the marginalised rural areas, not only in Africa, but also dotted around the world.

Keywords Rural small scale farmers · Agricultural mobile marketing (*m*-marketing) · Acceptance of technology · Sustainability

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Introduction and research contextualisation

The Fourth Industrial Revolution (4IR) disruptive technologies are going to unlock the potential for sustainable agricultural marketing information services dissemination innovation in agro-based emerging economies (Yingi et al. 2022) through facilitating the inter-linkages in the enhanced agricultural production processes (Anthony Jnr and Petersen 2021; McAfee and Brynjolfsson 2017; Nagar 2020). However, the effect of the novel pandemics such as the Corona Virus is forcing individuals to opt to go for the sustainable emerging technologies adoption as a gateway to convenience in a bid to access services such as agricultural mobile marketing (*m*-marketing). The devastating Corona Virus pandemic emanated in Wuhan, China, whereas of 1 July, 2021, there was a recording of 181,924,652 cases of the virus and 3,938,817 deaths confirmed (WHO 2021). Due to this, the proliferation of smart devices in the African continent has further pushed the need to increase mobile marketing service (Okocha and Adibi, 2020). Agricultural *m*-marketing is fast being accepted in Zimbabwe and other African states with Nigeria, Tanzania, South Africa leading as a result of its larger population base (UNCTAD 2019). Agribusiness organisations have since invested in the development of mobile marketing applications over the years (Owusu et al. 2020) in response to the demand for *m*-marketing as a result of changes caused by the volatile, uncertain, complex and ambiguous agribusiness environment (Nyagadza, Mazuruse et al. 2022). Challenges of *m*-marketing may include, but not limited to sufficiency issues related to maturity befitting disruption and whether there can be affordability to the costs faced for interoperability reasons (Micheler et al. 2019).

In Zimbabwe, rural small scale farmers are estimated to be 9, 655 with a mean of 148 hectares (ZimStat 2019). A snapshot background of the Marondera district, under Mashonaland East province of Zimbabwe, depicts it is dominated by cereal-legume-based farming system and maize is the major staple crop. The population is largely youthful with 68% of the total population aged below 35 (UNFPA 2022). Sandy to loamy soils dominate the target districts and mean annual rainfall ranges between 600 and 750 mm (ZimStat 2019). The district fall under region three which covers 72, 900km² (19% of total area). There is high propensity of long-term agricultural marketing growth and reduction of poverty (Mbengo and Phiri 2015). What triggered the need for the study is that these rural small scale farmers are partially involved in high income value chains and produce mainly for consumption and surplus is meant for business purposes, but the problem is mainly on how to market the latter effectively. Majority of these rural small farmers are facing serious difficulties in getting agricultural marketing information for their produce. Therefore, using the smart mobile phones for agricultural marketing information can be a panacea to this perennial challenge (Owusu et al. 2020). Furthermore, this is particularly true of the 4IR that has caught many African countries unaware and they are failing to cope with the speed with which the technological revolution is moving (Okocha and Adibi 2020).

Evidence from literature review depicts that researchers such as Owusu et al. (2020), Okocha and Adibi (2020), Mbengo and Phiri (2015) (from developing

countries), Changchit et al. (2017), Chong et al. (2012), Larforet and Li (2005), Kim et al. (2009) (from developed countries) have carried out research in almost similar areas associated with smart mobile phone for marketing information adoption intention which is very different from the current study. They could not proffer conclusions that link agricultural *m*-marketing and its acceptance with a perspective from a developing country like Zimbabwe. The current study shows that there are some provocative exceptions which arose from it as the conclusions seemed to contradict with the widely available conclusions related to agricultural marketing information access using smart mobile devices (Mbengo and Phiri 2015). The nature and scope of agricultural marketing information access by rural small scale was addressed and reasons for its existence were explored. Another gap is that prior research studies have applied different methodological applications which are quite distinctive from the currently applied methodology (Davis et al. 1989; Pushel et al. 2010). Majority of agricultural marketing information access research with an African context (Owusu et al. 2020, Mbengo and Phiri 2015) mainly applied qualitative or mixed research methodology, yet the current study uses a nomothetic quantitative methodological approach. This paves room for a new line of thinking, which diverges from the conventional approaches to agricultural marketing information access for rural small scale farmers in terms of research methodology. The study showed that UTAUT2 theoretical framework applied is fit for the purpose and proved to be more superior in terms of its relevancy, practicality and reality, as compared to other past research inquiries that have used different theories from information systems or information technology (such as Innovation Diffusion Theory (IDT) by Rogers (2003), Technology Acceptance Model (TAM) by Davis et al. (1989), the Theory of Planned Behaviour (TPB) Azjen (1991), the Decomposed Theory of Planned Behaviour (DTBP) by Pushel et al. (2010), the Unified Theory of Acceptance and Use of Technology (UTAUT) by Venkatesh et al. (2003). This was after a rigorous review and analysis by the researchers. Furthermore the current study depicts that agricultural marketing information access for rural small scale farmers using smart mobile phones concept is still emerging though old under the researched areas, with certain population based on region, gender, race, ethnicity, age and etic being central in this issue.

Therefore, in line with this research context presented, two main research objectives were raised: (i) to predict small scale farmers' mobile phone usage acceptance prognosticators for agricultural marketing information, and (ii) to test the impact of demographic characteristics of small scale farmers on intention to adopt mobile phone usage for agricultural marketing information access in Zimbabwe. In order to examine the research objectives and filling the literature gap, the researchers drew theoretical insights from a variety of academic and professional fields, and collected valid farmers' responses toward sustainable mobile agricultural marketing information adoption intention determinants amidst COVID-19 pandemic prevalence in Zimbabwe. The study adds to theoretical literature development by extending knowledge on the UTAUT2 theoretical framework since there is paucity of research that have directly applied the model in agricultural marketing and general agribusiness. Practically the study enhances the need for adoption of contemporary

technologies to solve the current challenges facing farmers in the marginalised rural areas, not only in Africa, but also dotted around the world. Having agricultural marketing information access through smart devices, such as mobile phones, makes it easier for rural small scale farmers to connect with their customers without so much hassles.

This research article is structured as follows: theory, literature review, hypotheses and research conceptual model development are tackled in the first section This is followed by a section on methodological delineations, then analysis of results, and finally the conclusions, research implications, limitations and future research directions are presented.

Theoretical underpinning

The current study uses the Unified Theory of Acceptance and Use of Technology (UTAUT) model as the theoretical modelling framework. The UTAUT2, has factors which influence the adoption of technology, which has been viewed as an important agenda for changing the qualities of a given technological service in order to make it more attractive towards its adoption (Kuisma et al. 2007). The UTAUT2 model extended by Venkatesh et al. (2012) provides a better explanation and fit to the current research study as it depicts behavioural intentions and technology use than the prior model(s). In line with technology acceptance, the current study adopts the Extended Unified Theory of Acceptance (UTA) and Use of Technology (UTAUT) (as applied by Chao, 2019) models to fill the explained gaps existing in literature. The major constructs in the UTAUT2 model in Fig. 1 (Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Hedonic Motivations (HM), Habitual Use (HU), Perceived Innovativeness (PI), Self-Service Technology (SSTs), Inconvenience (INC), Facilitating Conditions (FC), Automation (AUT), Perceived Privacy Risk (PPR), Smart Mobile Phones Usage Trust (SMPUT), and Smart Mobile Phones Usage Acceptance (SMPUA)) were suggested as direct determinants of rural small scale farmers' intention to use mobile phone for agricultural marketing information access. In conjunction with prior research, Trust has been viewed as a very important factor (Venkatesh et al., 2012) in determining small scale rural farmers' perception and intention to adopt smart mobile phones (Alalwan et al. 2016; Hanafizdeh et al. 2014; Luo et al. 2010; Zhou 2012). Justification for the use of UTAUT2 in the current research study is based on its application in technology adoption such as mobile applications (Chao 2019) in services marketing communications areas.

Literature review, hypotheses and conceptual model development

The current section presents the relevant literature reviewed in line with the study, hypotheses and research conceptual model development. The organisation approach of literature in the current study follows a systematic literature review, where the literature has been extensively researched and its quality is critically evaluated

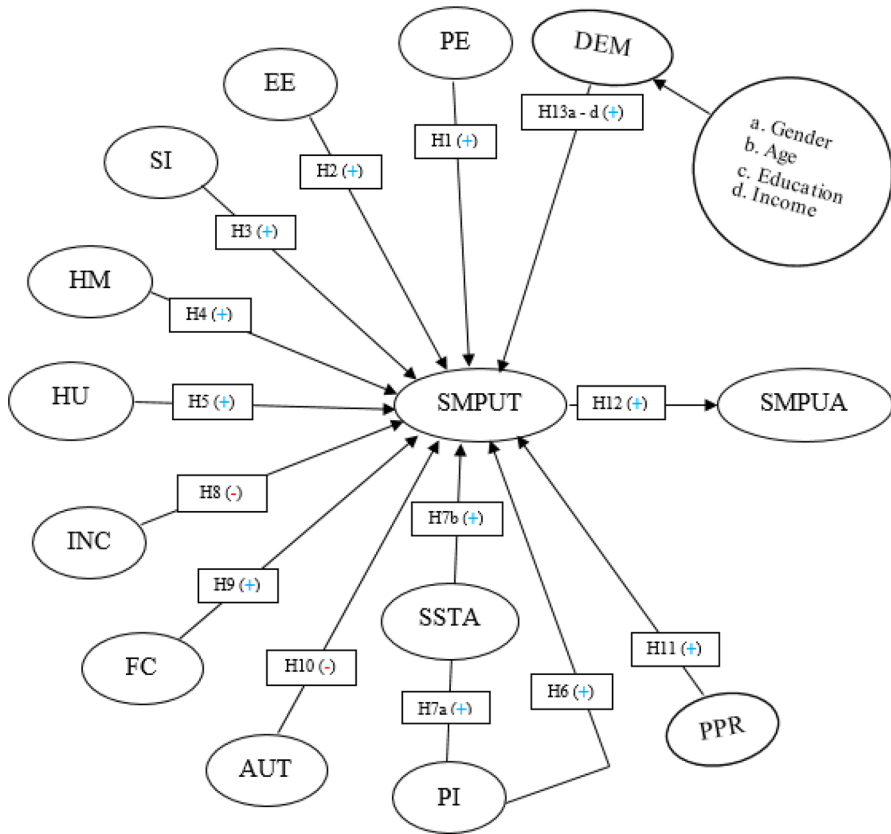


Fig. 1 Smart Mobile Phones Usage Acceptance (SMPUA) hypothesised conceptual model. *Source* Researchers’ conception (2022). Predictor variables—*PE* Performance Expectancy, *EE* Effort Expectancy, *SI* Social Influence, *HM* Hedonic Motivations, *HU* Habitual Use, *INC* Inconvenience, *FC* Facilitating Conditions, *AUT* Automation, *PPR* Perceived Privacy Risk, *PI* Perceived Innovativeness, *SSTA* Attitude towards Self-Service Technologies (SSTs). Mediator variable—*SMPUT* Smart Mobile Phones Usage Trust

(Nyagadza, 2022). The aim of using this literature organisation approach is to produce highest degree of thorough analysis, hypothesis development and subsequent conceptual model development and validation.

Performance expectancy

Evidence from research depicts that the greatest predictor of technology acceptance is performance expectancy (Khalilzadeh et al. 2017). Smart mobile phones’ interactivity and accessibility are essential characteristics of performance expectancy (Sundar and Kim 2019). Rural small scale farmers are highly motivated to accept new mobile technologies if they view them as more advantageous and functional in their daily agribusiness life (Alalwan et al. 2016; Davis et al. 1989; Venkatesh

et al. 2003). Previous research has depicted that mobile agricultural marketing information access has allowed rural small scale farmers to access more services ranges with proper flexibility in time and space (Alalwan et al. 2018; Gu et al. 2009; Luarn and Lin 2005). This indicates that rural small scale farmers' intention to use smart mobile phones for agricultural marketing information access is largely influenced by performance expectancy (Zhou et al. 2010). Due to the fact that agricultural *m*-marketing maybe used to assist in rural small scale farmers information access service, it is proposed that:

H₁ Performance expectancy positively influences rural small scale farmers' trust in smart mobile phones for agricultural marketing information access.

Effort expectancy

Effort expectancy can be viewed as the degree of easiness of use of technology system (Chao 2019). Basic antecedents of effort expectancy include ease of use and complexity. In the current study, effort expectancy refers to the belief and trust that the rural small scale farmers hold in the ease of use of smart mobile phones for agricultural marketing information (Sundar and Kim 2019). Rural small scale farmers' intention to accept the novel smart phones for agricultural marketing information access is not only determined by how much the use of the latter is positively valued but also by how much they require less efforts and not too difficult to use (Alalwan et al. 2018; Davis et al. 1989). However, for this to take place, it requires some certain skills and knowledge of operation from the rural small scale farmers (Alalwan et al. 2016). Effort expectancy is deemed to be a direct determinant of trust in smart mobile phones usage by rural small scale farmers (Hoque and Sorwar 2017). A number of research studies (Gu et al. 2009; Luarn and Lin 2005) have validated effort expectancy as having a crucial role in predicting rural small scale farmers' intention to accept smart mobile phones for agricultural marketing information access. Therefore, it is hypothesised:

H₂ Effort expectancy positively influences rural small scale farmers' trust in smart mobile phones for agricultural marketing information access.

Social influence

Smart mobile phones have great social influence or social presence. The social influence represents a sense of sociability, which in agricultural marketing information access affects the level of trust and usage intention in future (Yen and Chiang 2020) for rural small scale farmers. Social influence implies the psychological connection with rural small scale farmers who see the smart mobile phones as warm, personalised, trustworthy and sociable, leading to increased positive experience, feeling closer to human contact. The surrounding social environment include reference groups, family, friends, opinionated leaders, colleagues, general stakeholders (Alalwan et al. 2018; Zhou et al. 2010) etc. Encouragement by these can play a significant

role in shaping the rural small scale farmers' awareness and intention to adopt smart mobile technology for agricultural marketing information access (Alalwan et al. 2016; Martins et al. 2014; Riquelme and Rios 2010; Zhou et al. 2010). Hence, the following was hypothesised:

H₃ Social influence positively influences rural small scale farmers' trust in smart mobile phones for agricultural marketing information access.

Hedonic motivations

Rural small scale farmers find smart mobile phones as fun, enjoyment and as a diplomatic way of killing time. This is as a result of the motivation for satisfying hedonic and/or psychological needs that small scale rural farmers desire (such as socialising, information, entertainment and status) (Li and Mao 2015). The intrinsic utilities such as joy, playfulness, fun, entraining, and enjoyment have been included within the hedonic motivations in the same model (Venkatesh et al. 2012), as they drive the intention to adopt smart mobile phones by rural small scale farmers. This yields higher probability of creativity and uniqueness (Brown and Venkatesh 2005; Pushel et al. 2010; van der Heijden 2004). When smart mobile phones become more hedonically interactive, there is higher chance of being influential in determining small scale rural farmers' trust levels, and subsequently the intention to use them will be fostered (Lee and Choi 2017). We proposed that:

H₄ Hedonic motivations positively influence rural small scale farmers' trust in smart mobile phones for agricultural marketing information access.

Habitual usage

Smart mobile phones have systems applications which can be habitually used on a daily basis by customers, when making agribusiness transactions (Morosan and DeFranco 2016). Rural small scale farmers' habit is directly related to their past and present behaviour, which in turn affects their levels of trust in the smart mobile phones usage intention (Xu 2014). It is hypothesised that:

H₅ Habitual usage positively influences rural small scale farmers' trust in smart mobile phones for agricultural marketing information access.

Perceived innovativeness

Smart mobile phones perceived innovativeness is directly related to utilitarian gratification, whereby rural small scale farmers' technology utility needs are known to be information seeking and/or self-presentation (Papacharissi and Mendelson 2011). In this study, smart mobile phones perceived innovativeness is the willingness of customers to try out new technologies (Alalwan et al. 2018). Rural small scale farmers' tend to differ in the way they use information technology, as some adopt it and some

may delay adoption or reject it, due to the level of trust that they place. Therefore, we proposed that:

H₆ Perceived innovativeness positively influences rural small scale farmers' trust in smart mobile phones for agricultural marketing information access.

Attitude towards self-service technologies (SSTs)

If rural small scale farmers get the rightful experience they perceive smart mobile phones for agricultural marketing information access positively, their trust is increased if the innovativeness tally with their expectations (Dehghani 2018). Self-Service Technologies (SSTs) like smart mobile phones are more acceptable to the millennials than any other age group and their attitude is shaped by the associated trust. For this particular study, attitudes can be viewed as an antecedent of behavioural intention towards SSTs. Hence, experience and trust levels might be affected as a result of this issue. It is hypothesised that:

H_{7a} Perceived innovativeness positively influences rural small scale farmers' attitude towards Self-Service Technologies (SSTs).

H_{7b} Self-Service Technologies (SSTs) positively influence rural small scale farmers' trust in smart mobile phones for agricultural marketing information access.

Inconveniences

Due to the fact that rural small scale farmers may be better skilled in the human conversations imitations, hackers can capture the information, which may end up being a security risk concern to the concerned rural small scale farmers. Errors may increase and it may cause inconveniences to rural small scale farmers (Michels 2017). Such kind of inconveniences lead to phishing of confidential information since smart mobile phones use open internet protocols (Kar and Haldar 2016). As a result, we proposed that:

H₈ Inconveniences negatively influence rural small scale farmers' trust in smart mobile phones for agricultural marketing information access.

Facilitating conditions

Facilitating conditions can be viewed as the extent to which rural small scale farmers believe that the technical smart mobile infrastructure exists to enhance the functional use of the system (Venkatesh et al. 2003). Research has proved that people are more likely to be inclined to engage with technology that gives them experience which facilitates features through aesthetic cues (Han 2021). Many scholars contend that the perceptions of facilitating conditions by customers influence their intentions. Therefore, rural small scale farmers are motivated

to use smart mobile phones for agricultural marketing information access if they are sure that level of support service and resources available are compatible with other technologies already in use (Zhou et al. 2010). Further to this, smart mobile phones influence rural small scale farmers' trust and enjoyment perception, which in turn leads to intention to use the applications software for other transactions. Theoretically, this was supported by prior research studies (Alalwan et al. 2016; Zhou et al. 2010) which validated the notion that facilitating conditions predict the intention to adopt smart mobile technologies. We proposed that:

H₉ Facilitating conditions positively influence rural small scale farmers' trust in smart mobile phones for agricultural marketing information access.

Automation

Jobs with higher automation have proved to be of higher job insecurity and associated with poor health (Dehghani 2018). Further to this, technology has been seen as highly linked to displacement of people from work. Naturally, rural small scale farmers may have a negative attitude over the use of smart mobile phones in agricultural marketing information access as they are perceived to be predictively going to replace human service (Akst 2013). In line with this it leads to the following hypothesis:

H₁₀ Automation negatively influences rural small scale farmers' trust in smart mobile phones for agricultural marketing information access.

Perceived privacy risk

Perceived risk can be viewed as the smart mobile phones' uncertainty about the negative outcomes related to revealing of rural small scale farmers' personal information. Under normal circumstances rural small scale farmers are concerned about privacy issues when they do agricultural marketing transactions (Sundar and Kim 2019). Privacy and security trust in the smart mobile phones in agriculture is a major issue of concern, especially when dealing with personal information such as email addresses, cell numbers, names, or physical addresses (Sheehan 2018). Therefore, we proposed that:

H₁₁ Perceived privacy risk negatively influences rural small scale farmers' trust in smart mobile phones for agricultural marketing information access.

Trust and agricultural mobile marketing acceptance

Intention can be defined as the rural small scale farmers' subjective chance that they will act with an actual behaviour (Bae 2018). Trust levels have been operationalized

in prior research (Alalwan et al. 2018) as the rural small scale farmers' integrity, benevolence and ability in relation perception of smart mobile phones. Basing on this evidence in literature, we hypothesise that:

H₁₂ Trust positively influences rural small scale farmers' trust in smart mobile phones for agricultural marketing information access.

Customers' age, gender, trust and agricultural mobile marketing acceptance

Millennials have the largest rural small scale farmers and consumer group and being the initial digital-native generation, have a natural affinity for technologies (Dehghani 2018). The Gender Socialisation theory posits that rural small scale farmers' women are more apt to engage in pro-social behaviours than men (Yen and Chiang 2020) towards technology. Thus, a question is raised: will the young (men or women) rural small scale farmers use mobile phones for agricultural marketing information access as anticipated? Based on this, it is hypothesised that:

H_{13a} Gender positively influences rural small scale farmers' trust in smart mobile phones for agricultural marketing information access.

H_{13b} Age positively influences rural small scale farmers' trust in smart mobile phones for agricultural marketing information access.

H_{13c} Education positively influences rural small scale farmers' trust in smart mobile phones for agricultural marketing information access.

H_{13d} Income positively influences rural small scale farmers' trust in smart mobile phones for agricultural marketing information access.

Mediated relationships

Mediation effect may result in some of the relationship between the variables (Habitual use, inconvenience, social influence, hedonic motivations, female and male genders, attitude towards self-service technologies, perceived innovativeness, performance expectancy, effort expectancy and income, perceived privacy risk, education, facilitating conditions and automation, smart mobile phones usage trust and smart mobile phones usage trust) being statistically insignificant whilst some remain significant (Bae 2018; Alalwan et al. 2018; Wang and Lin 2017; Zhou et al. 2010). Therefore, we hypothesise that:

H_{14a} Habitual use and inconvenience positively mediates smart mobile phones usage trust.

H_{14b} Social influence and hedonic motivations positively mediates smart mobile phones usage trust.

H_{15a} Female and male genders positively mediates smart mobile phones usage trust.

H_{15b} Attitude towards self-service technologies and perceived innovativeness positively mediates smart mobile phones usage trust.

H_{16a} Performance expectancy, effort expectancy and income positively mediates smart mobile phones usage trust.

H_{16b} Perceived privacy risk, education and income positively mediates smart mobile phones usage trust.

H_{17a} Age1 and age2 positively mediates smart mobile phones usage trust.

H_{17b} Facilitating conditions and automation positively mediates smart mobile phones usage trust.

H_{18a} Smart mobile phones usage trust positively mediates smart mobile phone usage acceptance.

Based on the theoretical and literature review and posited hypotheses, the conceptual model supporting this study is illustrated in Fig. 1:

Methodology

The sample, design of the questionnaire and measures, as well as data collection methods applied in the research are explained in this section. Stretching of the data collection period was a result of covid-19 restrictions, which delayed the whole process. Due to objective nature of the research study, deductive logic and approach was applied to test the UTAUT2 model after practical statistical inferences. On the condition of nomothetic quantitative methodology, the researchers applied cross-sectional time horizon due to the fact that the research was limited to a specific time frame. Time horizons are needed for the research design independent of the research methodology used (Saunders et al. 2009).

Design of questionnaire and measures

Study constructs in Table 10 (Appendix 1) were measured using item scales adapted from literature specifically related to intention to use smart mobile phones by rural small scale farmers for agricultural marketing information access. The questionnaire was in English language, interview type and translation was made in local Shona language understandable to the small scale farmers in the target areas. Performance

Expectancy can be found in Venkatesh et al. (2012) and Melián-González et al. (2021). Effort Expectancy, Social Influence, Hedonic Motivations and Habitual Use (Venkatesh et al. 2012, Melián-González et al. 2021), Perceived Innovativeness have been developed from Parra-López et al. (2011) and Melián-González et al. (2021). Attitude towards SSTs (Dabholkar and Baggiozi 2002), Inconvenience (Hill et al. 2015; Robertson et al. 2016; Melián-González et al. 2021), Automation (Melián-González et al. 2021), Perceived Privacy Risk (Cheng and Jiang 2020; Sundar and Marathe 2010), Chatbots Usage Trust (Yen and Chiang 2020), Smart mobile phones usage Intention (Parra-López et al. 2011) were subjected to examination via Confirmatory Factor Analysis.

Sampling and data collection

The research study applied a cross-sectional survey of 490 small scale farmers conducted in Marondera town in Mashonaland East province of Zimbabwe (depicted in Fig. 2). Justification for the three selected towns is that these are the epicentres of agribusiness for rural small farmers with all year round good weather conditions necessary for agricultural productivity. The researchers divided the population of 600 potential respondents into more relevant and significant strata (Muposhi et al. 2021) based on subsets where a random sample was drawn from each of the strata (Saunders et al. 2009) such as the rural small scale farmers' profiles (low, middle



Fig. 2 Map of Zimbabwe Showing all provinces. Source Google Maps (2021)

and high income earning capacities) as well as the geographical locations (homesteads and/or villages) to which they belong. Stratified random sampling technique was applied due to its accuracy and easy-to-use advantages (Saunders et al. 2009). In order to determine the sample size, Krejcie and Morgan 1970 formula was applied, necessary to construct a confidence interval (generally + 5%) (Alalwan et al. 2018). The research study applied physical cross-sectional survey with the aid of 25 fieldworkers. A pilot study was conducted on 22 respondents using stratified probability sampling from local rural small scale farmers in the targeted areas. A total of 490 questionnaires were distributed, and 435 were returned. This gave a positive response rate of 88.78%. Among these questionnaires, 42 of them were spoiled and the rest (403) had valid responses fit for analysis. These respondents represented the recommended 5% of the research study sample. Participation was voluntary and the objectives of the study were explained to the participants in the research study before completing the questionnaire. To complete the questionnaire, the respondents took about 20 min on average. Females dominated males in the survey. Majority of the respondents (69.2 percent) were aged between 20 and 39 years. Most of the respondents (67.2 percent) had already earned at least an ordinary level certificate of education. Majority of the respondents (84.4 percent) were earning less than USD\$400 per month.

Common method variance

Common method variance refers to variance that is attributable to the measurement method rather than to the constructs the measures are supposed to represent (Podsakoff 2003). Although they are statistical strategies like the Harman's one factor test and Confirmatory factor analysis marker technique, the researchers decided the cautious approach which will maintain all the exogenous variables in the model without removing them. One of the easiest ways to increase the probability of response accuracy is to develop a good research information coversheet and set of instructions (Hair et al. 2015). Podsakoff et al. (2012) argue that the motivation increases if participants know how the information will be used or how it will benefit them or the organization (e.g. improve working conditions). Feedback may also motivate the respondents and thereby increasing accuracy. The researchers promised to provide feedback after the analysis was done. The survey was designed in a way that reduces monotony and boredom. Spending more time attending to the questions may result in poor accuracy. Promising feedback may also motivate greater accuracy. Similarly, keeping the survey short and minimizing redundant measures and overlap should help participants to give more accurate responses. The researchers made sure that the scale items are easy to understand and interpret. Words with multiple meanings in an item were avoided. Questions asked were simple and concise to avoid double-meaning. The respondents who participated in the survey were knowledgeable about the subject under study and they had experience. Common scale properties (e.g. type, number of scale points, anchor labels) increase common method bias (CMB) (Johnson et al. 2011). It is thought that response format similarity increases the likelihood that cognitions triggered in answering one question will be retrieved

to answer the following questions (Podsakoff et al. 2012). If possible, minimize the scale properties shared by measures of the predictor and criterion variables to reduce CMB. Apart from these criteria, the researcher also undertakes the Harman single factor test which is a post hoc procedure that is conducted after data collection to check whether a single factor is conducted for variance in the data (Cheng et al. 2010). The model might suffer from common method variance if the % variance is greater than 50%. The data was run in SPSS V 25.0 and the % variance was 59.2% which is above 50% and hence can cause the problem of common method bias.

Data analysis

Both descriptive and inferential statistics were used in analysing quantitative data from the questionnaire. Structural Equation Modelling (*SEM*) was used to test the posited hypotheses (Hair et al. 2019a). Descriptive statistical analysis was achieved through the functional application of charts, tables, graphs and diagrams, and this fed into inferential statistics (Field et al. 2012; Hair et al. 2011a). These included frequencies, mean, and standard deviation. Software packages used for data visualisation were Smart PLS and SPSS, version 3 and version 25, respectively. Exploratory Factor Analysis (*EFA*) was used to identify the underlying relationships between the variables measured (Chan and Idris, 2017; Hair et al. 2017). To assess adequacy of the measurement model, the researchers applied Confirmatory Factor Analysis (*CFA*) (Saunders and Thornhill 2009). The researchers also utilised Principal Component Analysis (*PCA*) to consider the total variance in the data (Gerald 2018; Hair et al. 2019a), and establishing minimum number of factors that will account for the maximum variance (Hair et al. 2013, 2019b). In addition, the Bartlett's test of sphericity was applied to examine the hypothesis that the variables were uncorrelated (Saunders and Thornhill 2009).

Reliability and validity

Reliability of each factor in the instrument was tested using Cronbach's alpha (α) (Malhotra 2010). Each value was required to be at least 0.5, as this is suggested to be a sufficient reliability score by Churchill (1979). Internal consistency was meant to measure the degree of interrelatedness of measurement items that were constructed to assess the uniformity (Maat et al. 2011). To assess validity, content, discriminant and predictive validities were tested. The researchers used content validity to look into the fitness and link of the research subjects to the theoretical underpinnings (Malhotra 2010). Furthermore, the researchers employed pre-testing and pilot approaches to enhance research instrument's content validity (Muposhi et al. 2021). The concept of construct validity used was made to check on the connections between items that were assessed and the concept under study (Malhotra 2010). To assess construct validity, average inter-item correlations were computed using Confirmatory Factor Analysis (*CFA*) (Chan and Idris 2017). To establish discriminant validity of the measurement model, the researchers employed Fornell and Lacker's

(1981), measure of Average Variance Extracted (AVE). All the factor loadings that were above 0.5 were considered (Fornell and Larcker 1981).

Ethical considerations

Ethical considerations related to participating hotel customers' privacy, informed consent, freedom of response, professionalism, integrity, accuracy and values of research have been adhered to by the researchers, in line with the provisions made by the Marketing Research Society (MRS) (2022). Due to this, the researchers were obliged to observe the practices that take note of the values and integrity of research by not making manipulations to ethical issues. They made sure that they upheld ethical considerations by maintaining integrity and professionalism about the morals of academic research. All this was done to cope up with social desirability bias to ensure creditable data collection.

Analysis and results

Sample adequacy and test of normality

The KMO result (0.901) indicated that the sample size was adequate, while Bartlett Test depicted ($p < 0.05$) there were significant relationships between the variables, leading to factor analysis suitability. Table 1 depicts the results.

Reliability analysis

Results from Table 2 indicate that Cronbach's alpha value ranges between 0.801 and 0.929, demonstrating that all the observed items are reliable and consistent. The mean and standard deviation were also presented in the study. Mobile phone chatbots usage trust had the highest mean of 4.28 meaning that many farmers were trusting the usage of mobile phones. Automation had the lowest mean of 2.10. Collier (2020) examined normality of the data using the kurtosis and skewness and suggested that data are recognized normally distributed if the ranges of skewness values are between -2 and $+2$, and the ranges of kurtosis values are between -10 and $+10$. Guided by this rule, the study results from Table 2 indicated the skewness values that ranged from 0.73 to 1.79 and kurtosis values ranged from 1.02 to 1.87 which was within the acceptable ranges.

Table 1 KMO and Bartlett's Test

Kaiser–Meyer–Olkin measure of sampling adequacy		.901
Bartlett's Test of Sphericity	Approx. Chi-Square	2142.513
	Df	26
	Sig.	0.000

Source Primary data (2022)

Table 2 Descriptive Statistics

Construct	Item	Descriptive statistics			Cronbach alpha	Result	Communalities
		Mean	SD	K _u			
Performance expectancy (PE)	PE1	4.23	1.12	.872	0.823	Reliable	0.871
	PE2			.880			
	PE3			.944			
	PE4			1.45			
Effort expectancy (EE)	EE1	4.27	1.04	1.23	0.844	Reliable	0.867
	EE2			1.64			
	EE3			.977			
Social influence (SI)	SI1	4.14	1.34	.761	0.806	Reliable	0.880
	SI2			.821			
	SI3			1.25			
Hedonic motivations (HM)	HM1	4.22	1.27	1.34	0.789	Reliable	0.875
	HM2			1.67			
	HM3			1.25			
Habitual user (HU)	HU1	4.24	1.13	0.87	0.835	Reliable	0.846
	HU2			1.34			
	HU3			1.25			
Perceived innovativeness (PI)	PI1	4.18	1.10	.956	0.811	Reliable	0.835
	PI2			.783			
	PI3			1.34			
Self-service technology (SSTA)	SSTA1	4.08	1.27	1.16	0.839	Reliable	0.871
	SSTA2			1.33			
	SSTA3			1.25			
	SSTA4			1.53			

Table 2 (continued)

Construct	Item	Descriptive statistics			Cronbach alpha	Result	Communalities
		Mean	SD	K _u			
Smart mobile phone usage acceptance (SMPUA)	SMPUA1	4.31	1.05	1.16	1.72	0.861	0.855
	SMPUA2			1.19	1.35		
	SMPUA3			1.48	1.50		
Inconvenience (INC)	INC1	2.12	1.04	1.28	1.52	0.726	0.846
	INC2			1.14	1.56		
	INC3			1.09	1.27		
	INC4			1.79	1.87		
Automation (AUT)	AUT1	2.10	1.02	0.87	1.02	0.718	0.801
	AUT2			0.98	1.13		
	AUT3			0.73	1.09		
Perceived privacy risk (PPR)	PPR1	4.23	1.33	1.05	1.85	0.818	0.836
	PPR2			1.32	1.56		
	PPR3			1.62	1.59		
Mobile phone chatbots usage trust (SMPUT)	SMPUT1	4.28	1.27	1.69	1.47	0.871	0.879
	SMPUT2			1.56	1.58		
	SMPUT3			1.43	1.77		
Income	Income1			1.35	1.25	0.723	0.807
	Income2	2.26	.87	0.87	1.12		
	Income3			0.91	1.19		
	Income4			0.89	1.47		

Table 2 (continued)

Construct	Item	Descriptive statistics			Cronbach alpha	Result	Communalities
		Mean	SD	S_k			
Facilitating conditions	FC1	4.16	1.41	1.28	1.42	Reliable	0.836
	FC2			1.37	1.42		
	FC3			1.41	1.63		
Education	Edu1	2.19	1.04	0.91	1.03	Reliable	0.872
	Edu2			0.82	1.06		
	Edu3			0.78	1.10		

Source primary data (2022)

Correlation analysis

Table 3 gives the inter-item correlation estimates: social influence and mobile phone usage trust ($r=0.613$), attitude towards self-service and mobile phone usage trust ($r=0.619$), attitude towards self-service and social influence ($r=0.527$), perceived privacy risk and mobile usage trust ($r=0.552$), perceived privacy risk and social influence ($r=0.324$), perceived influence and social influence (0.409), perceived influence and perceived privacy risk (0.457), performance expectancy and mobile phone usage trust (0.327), performance expectancy and attitude towards self-service ($r=0.317$), performance expectancy and perceived privacy risk (0.476), performance expectancy and perceived influence (0.409), income and mobile phone usage trust($r=0.410$), income and social influence ($r=0.426$), income and attitude towards self-service ($r=0.354$).

Convergent validity

The average variance extracted (AVE) values for convergent validity test across constructs ranged between 0.528 and 0.699 (>0.50), showing that the indicators assumed to measure the same construct sufficiently. High composite reliability is a very good indication that all your items constantly measure the same construct. The Composite Reliability ($CR \geq 0.60$) ranged from 0.794 to 0.897. From this information we can conclude that they could measure the latent variables. These outcomes support the validity of the measurements (See Tables 4, 5, 6).

Table 3 Correlation between constructs

Latent variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1.SMPUT	1													
2.SI	.613	1												
3.SSTA	.619	.527	1											
4.PPR	.552	.324	.543	1										
5.PI	.519	.409	.598	.457	1									
6.PE	.327	.420	.317	.476	.409	1								
7.Income	.410	.426	.354	.365	.428	.539	1							
8.INC	.321	.303	.301	.325	.307	.310	.318	1						
9.HU	.301	.529	.762	.619	.341	.486	.514	.639	1					
10.HM	.441	.434	.668	.629	.494	.588	.643	.702	.712	1				
11.FC	.509	.556	.516	.542	.487	.471	.531	.537	.501	.476	1			
12.Edu	.546	.574	.630	.587	.519	.603	.550	.421	.453	.429	.538	1		
13.EE	.839	.837	.875	.857	.837	.853	.822	.853	.863	.848	.434	.539	1	
14.AUT	.391	.405	.419	.417	.418	.387	.340	.421	.430	.396	.393	.342	.416	1

Source Primary data (2022)

Table 4 Convergent validity

Construct	Item	Factor Loading (FL)	FL ²	1 - FL ²	Number of indicators(n)	CR	AVE	Result
Mobile phone usage acceptance (SMPUA)	SMPUA1	.765	.585	.415	3	.834	.642	Achieved
	SMPUA2	.803	.645	.355				
	SMPUA3	.772	.696	.304				
Mobile phones usage trust (SMPUT)	SMPUT1	.712	.507	.493	3	.799	.571	Achieved
	SMPUT2	.809	.654	.346				
	SMPUT3	.743	.552	.448				
Social influence (SI)	SI1	.814	.663	.337	3	.854	.661	Achieved
	SI	.776	.602	.392				
	SI3	.847	.717	.283				
Self-service technology (SSTA)	SSTA1	.729	.531	.469	4	.837	.562	Achieved
	SSTA2	.673	.453	.547				
	SSTA3	.830	.689	.311				
	SSTA4	.758	.575	.425				
Perceived privacy risk (PPR)	PPR1	.845	.714	.286	3	.816	.656	Achieved
	PPR2	.779	.607	.493				
	PPR3	.804	.646	.554				
Perceived innovativeness(PI)	PI1	.854	.729	.271	3	.857	.667	Achieved
	PI2	.843	.711	.289				
	PI3	.749	.561	.439				
Performance expectancy (PE)	PE1	.823	.677	.323	4	.882	.651	Achieved
	PE2	.729	.531	.469				
	PE3	.849	.721	.279				
	PE4	.822	.676	.324				

Table 4 (continued)

Construct	Item	Factor Loading (FL)	FL ²	1 - FL ²	Number of indicators(n)	CR	AVE	Result
Income	Income1	.749	.561	.439	4	.817	.528	Achieved
	Income2	.684	.468	.532				
	Income3	.733	.537	.463				
	Income4	.739	.546	.454				
Inconveniences (INC)	INC1	.887	.787	.213	4	.875	.640	Achieved
	INC2	.834	.696	.304				
	INC3	.611	.373	.617				
	INC4	.838	.702	.298				
Habitual use (HU)	HU1	.723	.523	.477	3	.836	.675	Achieved
	HU2	.883	.78	.220				
	HU3	.764	.584	.416				
Hedonic motivations (HM)	HM1	.901	.812	.188	3	.874	.699	Achieved
	HM2	.771	.594	.406				
	HM3	.831	.691	.309				
Facilitating conditions (FC)	FC1	.872	.760	.240	4	.897	.687	Achieved
	FC2	.800	.640	.360				
	FC3	.768	.590	.410				
	FC4	.870	.757	.243				
Education	Edu1	.786	.618	.382	3	.834	.628	Achieved
	Edu2	.852	.726	.274				
	Edu3	.734	.539	.461				

Table 4 (continued)

Construct	Item	Factor Loading (FL)	FL ²	1 - FL ²	Number of indicators(n)	CR	AVE	Result
Effort expectancy (EE)	EE1	.749	.561	.439	3	.806	.582	Achieved
	EE2	.696	.484	.516				
	EE3	.838	.702	.298				
Automation (AUT)	AUT1	.718	.516	.484	3	.794	.561	Achieved
	AUT2	.676	.457	.543				
	AUT3	.843	.711	.289				

Source Primary data (2022)

Table 5 Fornell-Larcker criterion

Latent variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1.SMPUT	.756													
2.SI	.613	.813												
3.SSTA	.619	.527	.750											
4.PPR	.552	.324	.543	.820										
5.PI	.519	.409	.598	.457	.817									
6.PE	.327	.420	.317	.476	.409	.807								
7.Income	.410	.426	.354	.365	.428	.539	.727							
8.INC	.321	.303	.301	.325	.307	.310	.318	.800						
9.HU	.301	.529	.732	.619	.341	.486	.514	.639	.822					
10.HM	.441	.434	.668	.629	.494	.588	.643	.702	.712	.829				
11.FC	.509	.556	.516	.542	.487	.471	.531	.537	.501	.476	.836			
12.Edu	.546	.574	.630	.587	.519	.603	.550	.421	.453	.429	.538	.792		
13.EE	.719	.737	.715	.807	.801	.753	.622	.753	.763	.748	.434	.539	.763	
14.AUT	.391	.405	.419	.417	.418	.387	.340	.421	.430	.396	.393	.342	.416	.749
AVE	.571	.661	.562	.656	.667	.651	.528	.640	.675	.687	.699	.628	.582	.561

Source primary data (2022)

Table 6 Coefficient of determination (R^2), Variance Inflation Factor (VIF) and Tolerance

Variables	R Square	VIF	Tolerance
Mobile phones usage trust	0.987	76.92	.013
Self-service technology	0.977	43.48	.023
Mobile phone usage acceptance	0.975	40	.025

Source Primary data (2022)

Discriminant validity

Discriminant validity is a requirement in an instrument development that involves latent consstrct (Hamid et al. 2017). Develis (2017) referred to discriminant validity as divergent validity meaning that two concepts should show significant differences conceptually. It aims to prove that one construct is highly different from the other one (Voorhees 2015). Discriminant validity can be assessed through cross loadings, Heterotrait-monotrait (HTMT) and Fornell-Larcker criterion. However, in this research we used the Fornell-Larcker criterion. Average Variance Extracted (AVE) were matched with squared inter-construct correlations in an attempt to measure discriminant validity. It is a measure that compares the square root of each construct’s AVE with its correlations with all other constructs in the model. The diagonal values (in bold) are the square root of AVE, while other values are the correlations between respective latent construct its row and column. The square roots of AVE of the four latent constructs were greater than the inter-construct correlation and fulfilled the criteria of discriminant validity.

Assessment of the coefficient of determination and multicollinearity

Schumacher et al. (2016) define R^2 value as the percentage of variance in the variable that is accounted for by association in the independent variable groups. R^2 values of 0.75, 0.5 and 0.25 can be considered substantial, moderate, and weak respectively (Hair et al. 2011). Very high values of R^2 may result in the model overfitting the data and may result in a spurious relationship provided the R^2 value is greater than the Durbin Watson. In the current study, disconfirmation has an R^2 value of 0.57 which is explained by negative emotions. The predictor has a direct effect towards disconfirmation. The mobile phones usage trust has an R^2 value of 0.987, contributed by all the predictors in the model. Moreover, the self-service technology has an R^2 value of 0.977. The mobile phone usage acceptance has an R^2 value of 0.975 which is explained by mobile phones usage trust. Overall, the developed model has a substantial explaining power. Though high coefficient of determination values may result in a better fit for the model, it can also cause some problems.

Multicollinearity is one of the assumptions of structural equation modelling. Before judging the structural interactions collinearity, we have studied to make sure it does not bias the results. The Variance Inflation Factor (VIF) and tolerance is often used to evaluate collinearity of the predictors. Hair et al. (2011) noted that VIF values of 5 or above indicate critical collinearity issues among the variables whilst Collier (2020) noted that tolerance values (>0.10) are desirable. However, collinearity issues can also occur at lower VIF values of 3 (Becker et al., 2015). Ideally, the VIF values should be close to 3 and lower.

From the structural equation modelling results the VIF values for mobile phones usage trust, self-service technology and mobile phone usage acceptance were 76.92, 43.48 and 40, respectively. The tolerance values were below 0.10 meaning that multicollinearity was found to be a problem according to (Becker et al. 2015). There are various ways of solving multicollinearity such as merging the independent variables, dropping other variables in the model and also using the dimension reduction technique. The researchers decided to merge the independent variables since it retains all the constructs in the model. Though there are various techniques for dealing with multicollinearity, the researchers chose not to lose the information by combining that belong to a common category (Hair et al. 2010) (See Fig. 3).

The bootstrap method was used to validate the significance of the path coefficients by comparing β values among all the paths. However, β value has to be tested for its significance level through t -value test. The test is accomplished by performing nonparametric bootstrapping technique (Kumar et al. 2016). Bootstrapping technique calculates t -value by creating pre-specified number of samples. Hair et al. (2011) suggested that acceptable t -values for a two tailed are 1.65 (significance level=10 percent), 1.96 (significance level=5 percent), and 2.58 (significance level=1 percent). In Table 7 the following path were statistically significant: SI+HM \rightarrow SMPUT ($\beta = 0.228, p=0.002$), SSTA+PI \rightarrow SMPUT ($\beta = 0.347, p=0.000$), PPR+Education+Income \rightarrow SMPUT ($\beta = 0.069, p=0.007$), PE+EE \rightarrow SMPUT ($\beta = 0.584, p=0.000$), FC+AUT \rightarrow SMPUT ($\beta = 0.075, p=0.003$) and SMPUT \rightarrow SMPUA ($\beta = 0.794, p=0.000$). The following path

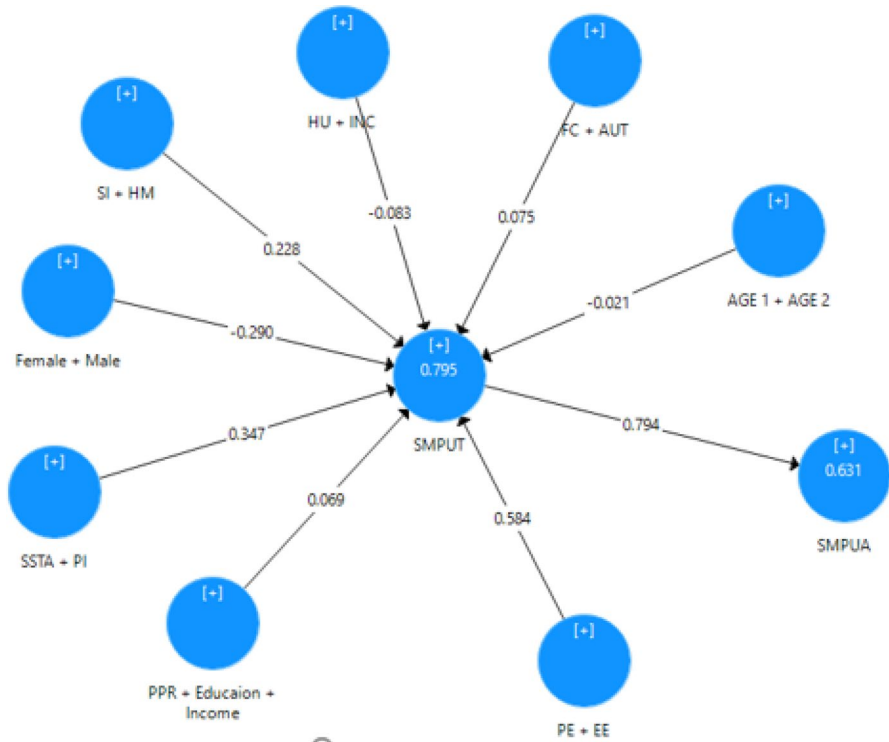


Fig. 3 Final Structural Hypothesized Model. *Source* Researchers’ conception (2022). *NB* AGE 1 (18–30) years and AGE 2 (> 30) years

Table 7 Results of bootstrapping

Path	Path Coeffi- cients (β value)	<i>t</i> -value	<i>p</i> -value	Significance level
SI + HM → SMPUT	.228	3.127	.002	Significant
Female + Male → SMPUT	-.290	0.718	.180	Not Significant
SSTA + PI → SMPUT	.347	3.904	.000	Significant
PPR + Education + Income → SMPUT	.069	2.816	.007	Significant
PE + EE → SMPUT	.584	4.831	.000	Significant
FC + AUT → SMPUT	.075	2.846	.003	Significant
AGE 1 + AGE 2 → SMPUT	-.021	1.083	.067	Not significant
SMPUT → SMPUA	.794	6.940	.000	Significant
HU + INC → SMPUT	-.083	1.384	.093	Not significant

Source Primary data (2022)

were statistically insignificant: Female + Male → SMPUT ($\beta = -0.290, p = 0.180$), AGE 1 + AGE 2 → SMPUT ($\beta = -0.21, p = 0.067$) and HU + INC → SMPUT ($\beta = -0.083, p = 0.093$).

Mediation effect analysis (Sobel's test)

Table 8 presents the results of testing specific indirect effects that reflect the hypothesized indirect relationships. From the analysis in Table 8 showing indirect and indirect relationship, there was no change in terms of the significance of the hypotheses. The only notable change was the reduction in the beta value, and this indicates the existence of a partial mediation. However, the Sobel's test tends to be criticized. From the analysis in Table 8, the path $SI + HM \rightarrow SMPUT \rightarrow SMPUA$, there is the product of 0.228 and 0.794 which are beta values for $SI + HM \rightarrow SMPUT$ and $SMPUT \rightarrow SMPUA$, respectively that is 0.228×0.794 results in 0.181. Further to this, the relationship between effort expectancy and mobile phone usage acceptance, is significantly mediated by mobile phones usage trust ($\beta = 0.286, p < 0.001$). Mediation effect may result in some of the relationship between the variables being statistically insignificant whilst some remain significant. From the analysis, it shows in both a direct and indirect relationship that there was no change in terms of the significance of the constructs. The confidence interval also confirms the results since the interval of the beta value excludes zero.

Coefficient of determination (R^2), VIF, effect sizes (F^2) and predictive relevance (Q^2)

Schumacher et al. (2016) define R^2 value as the percentage of variance in the variable that is accounted for by association in the independent variable groups. R^2 values of 0.75, 0.5 and 0.25 can be considered substantial, moderate, and weak, respectively (Hair et al. 2011). Very high values of R^2 may result in the model overfitting the data and may result in a spurious relationship provided the R^2 value is greater than the Durbin Watson. In the current study, disconfirmation has an R^2 value of 0.57 which is explained by negative emotions. The predictor has a direct effect towards disconfirmation. The mobile phones usage trust has an R^2 value of 0.795, contributed by all the predictors in the model. Moreover, mobile

Table 8 Mediation analysis (Sobel's test)

Path	Path Coef- ficients (β value)	t-value	p-value	Significance level
SI + HM \rightarrow SMPUT \rightarrow SMPUA	0.181	3.920	.000	Significant
Female + Male \rightarrow SMPUT \rightarrow SMPUA	- 0.230	1.073	.170	Not significant
SSTA + PI \rightarrow SMPUT \rightarrow SMPUA	0.276	4.281	.000	Significant
PPR + Education + Income \rightarrow SMPUT \rightarrow SMPUA	0.055	2.874	.000	Significant
PE + EE \rightarrow SMPUT \rightarrow SMPUA	0.464	6.317	.000	Significant
FC + AUT \rightarrow SMPUT \rightarrow SMPUA	0.060	2.936	.000	Significant
AGE 1 + AGE 2 \rightarrow SMPUT \rightarrow SMPUA	-0.017	1.402	.063	Not significant
HU + INC \rightarrow SMPUT \rightarrow SMPUA	-0.066	1.268	.092	Not significant

Source Primary data (2022)

phone usage acceptance has an R^2 value of 0.631 which is explained by mobile phones usage trust. Overall, the developed model has a moderate to substantial explaining power.

Multicollinearity was also examined in the final model. The Variance Inflation Factor (VIF) and tolerance is often used to evaluate collinearity of the predictors. Hair et al. (2011) noted that VIF values of 5 or above indicate critical collinearity issues among the variables whilst Collier (2020) noted that tolerance values (> 0.10) are desirable. However, collinearity issues can also occur at lower VIF values of 3 (Becker et al. 2015). Ideally, the VIF values should be close to 3 and lower. From the structural equation modelling results the VIF values for mobile phones usage trust and mobile phone usage acceptance were 4.88 and 2.71, respectively. The tolerance values were above 0.10 meaning that multicollinearity was not a problem according to (Becker et al. 2015).

The size of the Q^2 effect allows the evaluation of how an exogenous construct contributes to an endogenous latent construct Q^2 as a measure of predictive relevance, which can be small (0.02), medium (0.15) or large (0.35). The Q^2 values for this study model (0.404 and 0.348) were higher than the threshold limit and supports that the path model's predictive relevance was adequate for the endogenous construct. An Effect Size $f^2 \leq 0.30$, $0.3 < f^2 \leq 0.50$, and $f^2 > 0.50$ is thought to represent a weak, moderate and strong effect, respectively (Burnett et al., 2006). From this study, the effect size is strong according to Burnett et al. (2006). The final model has a moderate to strong effect (See Table 9).

The standardised root mean square residual (SRMR)s

Table 10 shows that this model's SRMR was 0.07, which exposed that this study model had a good fit, whereas the *Chi*-Square was equal to 1634.23 and NFI equal to 0.825 was also measured (See Table 11).

Overall assessment

The GoF value for this study is 0.669 (in Table 8) which is above 0.36 as indicated. This proves that the developed model is large in explaining the issues of mobile phone usage acceptance for accessing agricultural marketing information by rural small scale farmers.

Table 9 Coefficient of determination (R^2), Effect sizes (F^2) and predictive relevance (Q^2)

Variables	R Square	Q^2	Effect sizes (F^2)	VIF	Tolerance
Mobile phones usage trust	0.795	0.404	0.72	4.88	0.205
Mobile phone usage acceptance	0.631	0.348	0.36	2.71	0.369

Source primary data (2022)

Table 10 Model fit summary

	Estimated model
SRMR	0.07
d_ULS	1.621
d_G1	0.824
d_G2	0.743
Chi-Square	1634.23
NFI	0.825

Source primary data (2022)

Table 11 Goodness of Fit Index calculation

Construct	AVE	R ²
PE	0.651	
EE	0.582	
SI	0.661	
HM	0.699	
HU	0.675	
INC	0.640	
Income	0.528	
FC	0.687	
Education	0.628	
AUT	0.561	
PI	0.667	
PPR	0.656	
SSTA	0.562	
SMPUA	0.642	0.631
SMPUT	0.571	0.795
AVE	0.627	
AVE × R ²	0.447	
GoF	0.669	

Source primary data (2021)

Discussion

As depicted in Table 6, the paths indicated majority of them were positive such as age 1 and mobile phones usage trust, effort expectancy and mobile phones usage trust, facilitating conditions and mobile phones usage trust, hedonic motivations and mobile phones usage trust, habitual use and mobile phones usage trust, male

and mobile phones usage trust, performance expectancy and mobile phones usage trust, performance innovativeness and mobile phones usage trust, performance innovativeness and self-service technology, perceived privacy risk and mobile phones usage trust, social influence and mobile phones usage trust, mobile phones usage trust and mobile phone usage acceptance, self-service technology and mobile phones usage trust. Moreover, some of the following relationships were statistically insignificant: automation and mobile phones usage trust, age 2 and mobile phones usage trust, education and mobile phones usage trust, female and mobile phones usage trust, inconveniences and mobile phones usage trust, incomes and mobile phones usage trust. Moreover, some explanatory combinations were contributing less to the model, for example, gender and usage trust and gender and usage intention. Removing variables with low beta values improved the statistical significance of some variables though the effort may distort the researchers' intention (Nyagadza et al. 2022a, b). Since more than 50% of the explanatory variables had a positive effect, we can conclude that the interaction between the predictors were significant (Alalwan et al. 2015). From the analysis in Table 7 showing indirect and indirect relationship, there was no change in terms of the significance of the hypotheses. The only notable change was the reduction in the beta value, and this indicates the existence of a partial mediation. However, the Sobel's test tends to be criticized. From the analysis in Table 7, the path AUT and SMPUT and SMPUA, there is the product of 0.043 and 0.998 which are beta values for AUT and SMPUT and SMPUT and SMPUA, respectively that is 0.043×0.998 results in 0.043. Further to this, the relationship between effort expectancy and mobile phone usage acceptance, is significantly mediated by mobile phones usage trust ($\beta = 0.286$, $p < 0.001$). In addition to this, in line with the mediation analysis in Table 8, the path SI + HM \rightarrow SMPUT \rightarrow SMPUA, there is the product of 0.228 and 0.794 which are beta values for SI + HM \rightarrow SMPUT and SMPUT \rightarrow SMPUA, respectively that is 0.228×0.794 results in 0.181. The relationship between effort expectancy and mobile phone usage acceptance, is significantly mediated by mobile phones usage trust ($\beta = 0.286$, $p < 0.001$). Mediation effect may result in some of the relationship between the variables being statistically insignificant whilst some remain significant. The confidence interval also confirms the results since the interval of the beta value excludes zero. From the analysis, it shows in both a direct and indirect relationship that there was no change in terms of the significance of the constructs.

If rural small scale farmers get the rightful experience, they perceive smart mobile phones for agricultural marketing information access positively. Their trust is increased if the innovativeness tally with their expectations (Dehghani 2018). Mediation effect may result in some of the relationship between the variables being statistically insignificant whilst some remain significant. Rural small scale farmers are highly motivated to accept new mobile technologies if they view them as more advantageous and functional in their daily agribusiness life (Alalwan et al. 2016; Davis et al. 1989; Venkatesh et al. 2003). This is as a result of the motivation for satisfying hedonic and/or psychological needs that small scale rural farmers desire (such as socialising, information, entertainment and status) (Li & Mao 2015). Hence, experience and trust levels might be affected as a result

of this issue (Morosan and DeFranco 2019). Theoretically, this was supported by prior research studies (Alalwan et al. 2015; 2016; Zhou et al. 2010) which validated the notion that facilitating conditions predict the intention to adopt smart mobile technologies. Under normal circumstances, rural small scale farmers are concerned about privacy issues when they do agricultural marketing transactions (Sundar and Kim 2019). Trust levels have been operationalized in prior research (Alalwan et al. 2018) as the rural small scale farmers' integrity, benevolence and ability in relation perception of smart mobile phones. From the analysis, it shows in both a direct and indirect relationship that there was no change in terms of the significance of the constructs. Ideally, the VIF values should be close to 3 and lower. From the structural equation modelling results, multicollinearity was found to be a problem since the VIF values were above 5 according to (Becker et al., 2015).

Theoretical, practical and future research implications as well as limitations of the study findings are discussed in the following sections.

Theoretical implications

The major theoretical contribution of our research is that, unlike previous studies, the current study is anchored on the notion of investigating how rural small scale farmers (users) intend to use mobile phones sustainably in the context of a developing country, Zimbabwe. Thus, the current study significantly extends existing knowledge, which has not been effectively developed in the Zimbabwean context. The model developed in the current research study has managed to comprehensively integrate predictors from the existing literature, in connection with exploratory, empirical, conceptual and anecdotal literature conducted in the mobile phones research stratification. The study goes further beyond what Venkatesh et al. (2012) and Alalwan et al. (2017) proposed in UTAUT2 by adding Trust, Self-service Technologies (SSTs), Habitual Use and Automation as constructs, leading to development of novel causal paths in the model. A results comparison with the extant literature is anchored on the hypothetical context incubated to address the main research objectives. In line with this notion, it became apparent that the model applied in this research is more relevant due to the fact that most of the theories and models from the information systems or information technology literature have a context of the organisations (for example TAM and UTAUT). These theories are the Innovation Diffusion Theory (IDT) (Rogers, 2003) supported by Lin (2011) and Kim et al. (2009), Technology Acceptance Model (TAM) (Davis et al. 1989) noted by Gu et al. (2009), the Theory of Planned Behaviour (TBP) (Ajzen 1991) applied by Luarn and Lin (2005), the Decomposed Theory of Planned Behaviour (DTBP), Pushel et al. (2010), the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al. 2003) as noted by Zhou et al. (2010). The UTAUT2 in the current context has been applied with a user experience context with a focus on the rural small scale farmers' use of smart mobile phones for agricultural marketing information access. This is due to difference between the contexts in terms of ways of application and how the elements used can build rural small scale farmer's intention and

behaviour towards technology acceptance. Ultimately, it led to the adoption of the UTAUT2 model to anchor the study, as the appropriate model, with a user (rural small scale farmer) context (Venkatesh et al. 2012) in a developing country. Smart mobile phones acceptance study is a complicated phenomenon which may require more than one model to test its validity and reliability, than just using a single model like the UTAUT2 theoretical model explicated in the current study.

Practical implications

Our research's practical implications are for agribusiness industry and management. The digitalisation era has compromised the ability of individual rural small scale farmers in low resource settings in Zimbabwe to stamp their market and value chain access footprint, and sustain effective control and movement of their output within their borders profitably. This is stretching and straining the ability of these farmers even in other developing countries to defend their territorial integrity given that the technologically powerful commercial farmers are going over bound and making major profits through enhanced technologies. The mobile phones producers need to optimise the production of the smart mobile phones which should fit the needs of rural set ups and the costs related. Digitally connected smart farming technologies such as smart mobile phones with intelligent systems, shall revolutionize and optimise digital agricultural markets and supply chains of Zimbabwe and beyond, with interconnection of network systems. From a pragmatic perspective, the statistical results indicate the need for support of important role of the factors applied in the current model: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Hedonic Motivations (HM), Habitual Use (HU), Perceived Innovativeness (PI), Self-Service Technology (SSTs), Inconvenience (INC), Facilitating Conditions (FC), Automation (AUT), Perceived Privacy Risk (PPR), Smart Mobile Phones Usage Trust (SMPUT), and Smart Mobile Phones Usage Acceptance (SMPUA). Hence, these factors are deemed to be the mainstay of attention of any entity with an endeavour to instigate the desire for adoption of smart mobile phones for agricultural marketing information access by rural small scale farmers (Alalwan et al. 2017). In the short, adoption and use of the smart mobile for agricultural marketing information access will help rural small scale farmers to significantly reduce transaction costs of accessing input and produce markets, hence raising targeted revenues. It is expected that the short-term benefits will be invested in the long-term hence ensuring sustained income for the rural small scale farmers. Further to this, the research has determined useful contributions to agricultural marketing and communications practice and implications for pushing the agenda of sustainable mobile marketing in Zimbabwe, as well as its usage in uncertain times. The study offers valuable insights on how to achieve sustainable agricultural *m*-marketing customer base. Collaborative rural small scale farmers' education campaigns and marketing communications promotional efforts by agribusiness firms offering agricultural *m*-marketing are necessary in risk reduction perception (Venkatesh

et al. 2012). This may shape confidence and trust in the agribusiness system and agro-corporates' brand images.

In addition, practically, the study indicates that the use of SSTs by rural small scale farmers using smart mobile devices will enhance customers' perception towards mobile marketing for agricultural produce. This will improve and enhance agricultural marketing information access required by rural small scale farmers (Simintras et al. 2014). The adoption of smart mobile phones will foster social inclusion of underserved agricultural rural small scale farming communities, such as disabled persons, minority ethnic groups and those in other remote rural areas. Rural small scale farmers from Zimbabwe shall benefit from this adoption, where the districts are dominated by cereal-legume-based farming system and maize is the major staple crop. This is so because these farmers are partially involved in high income value chains and produce mainly for consumption. A right based approach that epitomises women, as claim-holders will be adopted at the inception of the project to ensure that no one is left behind. The gender gaps prevalent in most farming communities will be closed by the smart mobile phones digital knowledge acquisition and skills development. There is high propensity of long-term agricultural growth (high value cash crops and room for off-farm income generating activities) and reduction of poverty.

Study limitations, future research implications and conclusion

The study has limitations which may affect the generalisability of the results since they can only be applied to the population and country or area studied under the COVID-19 pandemic situation. Complementary research studies can be done in other parts of the world to be able to come up with cross-cultural comparisons as well as methodological validation. A fairly bigger sample and more accurate sampling plan may be needed in future to improve the study. Future research studies can include evaluating other relevant theoretical frameworks in testing rural small scale farmers' sustainable agricultural m-marketing acceptance theory determinants.

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Conflict of interest The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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