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Willing to be the change: Perceived drivers and barriers to participation in urban smart farming projects

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ABSTRACT

Psychological research on perceptions on urban smart farming is scarce, especially in a Global South context. To reach wide acceptance of urban smart farming and create effective strategies for the implementation of this innovative technology, we need insights into people's perceptions. In this article, we investigate the factors that motivate or hinder people to engage in community-led urban smart farming projects. We present a systematic assessment of perceived drivers and barriers for urban smart farming, based on a survey study in three African countries, Nigeria, South Africa and Zambia. Using multiple regression analysis, we could identify country-specific drivers and barriers. People's demographics have been found to play less of a role in predicting intentions to be involved in urban smart farming projects. We recommend considering the human dimension when promoting innovative technologies such as urban smart farming and encourage practitioners to assess each region individually when promoting innovative farming techniques.

KEYWORDS

Urban smart farm; agriculture; drivers; barriers; local community; Africa

Introduction

Urban smart farming is a concept that uses innovative technologies for food production based on the principles of circular economy in an urban context. This technological innovation facilitates food production in close proximity to the end consumer with minimal use of water, energy and land, which is in line with the core principles of sustainable development and especially Sustainable Development Goal 2, Zero Hunger (Gil et al., 2019; Musa & Basir, 2021). The urban smart farming methodology can be applied in abandoned buildings and thereby contribute to food security, carbon emission savings, the minimization of potential crime and community cohesion, as well as, a reduction in vectors of diseases (Audate et al., 2019). Not much is yet known about the willingness to engage in urban smart farming projects among local communities in Africa, a research gap this article will address.

More than 250 million undernourished people are living in Africa with numbers rising more rapidly than anywhere else in the world (Momberg et al., 2021). African metropolitans are growing rapidly into inefficient, unsustainable, resource-starved systems. This negatively affects people's health, well-being, quality of life, as well as overall economic development. As stated in SDG 2, food, as a key resource, needs to be produced and managed more sustainably, ideally on a local level (United Nations, 2020) to make nutritious and sufficient food accessible for everyone, all year round. In recent years, the COVID-19 pandemic has negatively affected the levels of people suffering under

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Supplemental data for this article can be accessed online at https://doi.org/10.1080/07352166.2023.2232060 malnutrition, for example, triggered by disruptions in food supply chains, an altered food environment and higher prices (Suri, 2021).

In recent years efforts have been made to increase the effectiveness of agriculture as such, as well as to use urban environments as agricultural areas. Technological innovations have led to the emergence of smart farming, defined as the utilization of information and communication technologies in the agricultural sector (Wolfert et al., 2017). Successful applications in sub-Saharan Africa include mobile phone applications (Makoye, 2013), precision agriculture (Onyango et al., 2021), the utilization of the Internet of Things (Routray et al., 2019) and artificial intelligence (Mohamed et al., 2021). Successful urban agriculture projects include community gardening (Battersby & Marshak, 2013), vertical farming (Gumisiriza, Kabirizi et al., 2022) and rooftop farming (Hugo et al., 2021). The aim of this study is to gain insights into the user perceptions influencing the motivation to engage in urban smart farming. To the authors' best knowledge previous studies have not explored this in the context of Africa, where urban smart farming projects are scarce. Exploring user perspective before introducing a new technology is important in order to overcome potential perceived barriers and to strengthen potential drivers (Neef et al., 2023). Including these perceptions already at an early stage fosters acceptance and engagement and finally contributes to unfold the full potential of urban smart farming.

In the following sections, we will first introduce our study locations and formulate specific research questions. Then, we discuss the benefits of urban smart farming before looking at relevant perceptions around urban smart farming from a psychological perspective (i.e., drivers and barriers). We will describe the present study in more detail, including the selected countries, the sample, the questionnaire used and our method of analysis. Afterward, the results, sorted by countries and identified drivers and barriers, will be presented individually before being brought together and discussed against the background of related literature. Finally, practical implications for practitioners and policymakers are derived based on the results and discussion.

The current study

This study is part of the Royal Society Funded project "Evaluating the role of urban smart farming on enhancing the sustainability of food production in African metropolitans." The aim was to assess the level and profile of people's intentions to get involved in a local urban smart farming project as well as to identify perceived motivating factors (i.e., drivers) and hindering factors (i.e., barriers) for these intentions in three African countries, South Africa, Nigeria and Zambia. We decided to choose three countries to reach a broad audience and to obtain country-specific, well-founded findings identifying commonalities and differences. We specifically chose South Africa, Nigeria and Zambia to provide a cross-section of the lower middle-income to upper middle-income countries in sub-Saharan Africa with a variety of urban conditions, environments and agriculture and thereby strengthen the research on urban smart farming in the Global South. Perceptions about drivers and barriers have been assessed through co-developed survey questionnaires. Two research questions were formulated, which will be answered in this article. No directed hypotheses have been formulated for this study as it was of explorative nature and the first attempt to investigate the importance of different drivers and barriers in a quantitative and comparative manner.

RQ1: How can intentions to engage in urban smart farming be characterized in South Africa, Nigeria and Zambia?

RQ2: Which perceived drivers and barriers are most relevant for the intention to engage urban smart farming in South Africa, Nigeria and Zambia as well as across all three countries?

Objective benefits of urban smart farming

Urban smart farming could be a potential mechanism to achieve sustainable and resilient food production in cities. They can also give new life and meaning to buildings that have lost their purpose. Especially after the COVID-19 pandemic lifestyles and business models worldwide have changed (Agustin et al., 2022). The new emphasis on virtual channels of communicating, learning and doing business leaves many buildings deserted (Richter et al., 2021). These abandoned buildings often develop into locations of crime such as drug trafficking (Tiberio et al., 2018). Repurposing these idle buildings to locations of community-managed indoor, urban smart farms might be a way to avoid criminal groups gathering in these places and make them a location of value creation. Urban farming has been shown to be a valuable approach to reducing illicit drug use in HIV patients and also to improve their overall well-being through community-based activities (Shacham et al., 2012). Another benefit of urban smart farming is that they provide room for the development of a sense of community and ownership (Grebitus, 2021). Contributing to urban smart farming projects is also an opportunity to develop relationships with others in the community and new skills (Duchemin et al., 2008). Especially for people who feel isolated, community gardens can provide room for regular social interactions, which makes the initiative particularly timely during and after the global pandemic. Furthermore, caring for plants and eventually harvesting edible crops can create a feeling of ownership, self-efficacy and pride (Grebitus, 2021; Sonti et al., 2016) and thereby contribute not only to physical but also mental health benefits (Harada et al., 2021). Specifically in Southern African cities, accessing land is often difficult and current urban agriculture is mostly unregulated with many people cultivating land without legal ownership or access. Controlled urban smart farming thus could also provide people with legal opportunities to engage in efficient urban agriculture (Jagganath, 2021).

Despite these benefits of urban smart farming, its prevalence in African cities is still low. The success of any innovation depends not only on its objective benefits but also on the perception thereof within the target audience. In this article, we therefore step away from objective benefits of urban smart farming and instead investigate key *perceived* drivers and barriers to be part of urban smart farming projects within the population of the three African countries studied in this article. By exploring how different perceived advantages and disadvantages affect people's intentions in different countries we can make specific recommendations of how to best communicate, introduce and implement new urban smart farming projects. Li et al. (2020) found that perceived benefits and risks influence the adoption of urban smart farming technologies in northern China. However, the authors do not specify which benefits or risks their participants thought about.

In the following, we will provide an overview over perceptions around urban smart farming that have been mentioned in the literature so far and conceptualize them into a basic model before assessing the relevance of all these drivers in selected African countries (Nigeria, Zambia and South Africa) as well as across countries.

Perceptions on urban smart farming

To identify what is perceived to be the key drivers and barriers for their engagement in urban smart farming projects and to then use this to encourage commitment of policymakers, businesses and communities alike, relevant literature around urban farming in general as well as urban smart farming has been reviewed. The selection of barriers and drivers that have been identified in the literature review is visualized in Figure 1.

When it comes to published research focusing on perceived benefits and barriers of urban smart farming in specific (meaning urban farming using smart, data-driven solutions, which rely on technology to optimize and customize production), evidence is relatively scarce compared to research focusing on urban farming more generally (meaning all types of agriculture taking place in urban environments such as backyard gardens, tactical gardens, street landscaping, forest gardening,

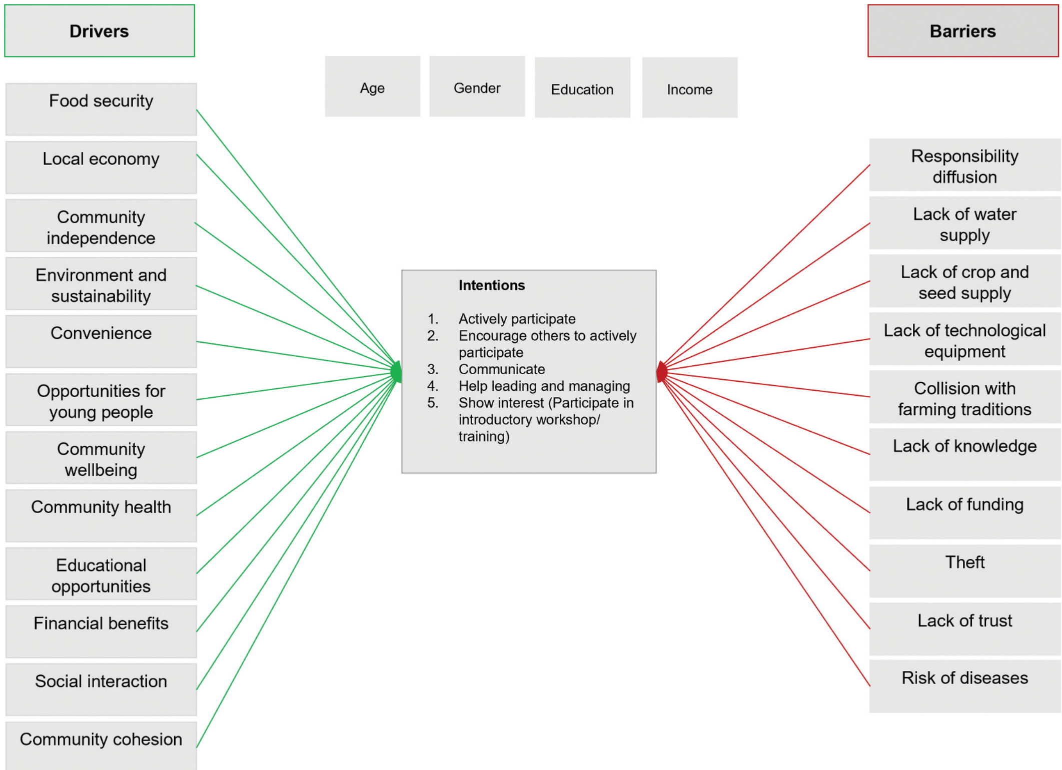

Figure 1. Identified concepts separated into drivers and barriers for intentions to engage in urban smart farming projects.

greenhouses, rooftop gardens and more). So far, most of the published research is focusing on populations located in the Global North.

Perceived drivers to engage in urban smart farming

According to the reviewed literature, the perceived benefits of urban smart farming mainly revolve around food security, nutrition, physical and mental health as well as social capital (Audate et al., 2019). Further positive associations people mention in relation to urban smart farming are that it contributes to community well-being in general (Campbell & Rampold, 2021; Chimbwanda, 2016; Knegtel, 2014; Tiraieyari & Krauss, 2018), career opportunities (Grebitus, 2021; Grebitus et al., 2020), opportunities to socialize with others and independence from food producers (Chimbwanda, 2016). Perceived health and well-being benefits are often mentioned in connection with accessibility of fresh and local food as well as the equality aspect of directly providing nutrition to people in need (Grebitus et al., 2020; Knegtel, 2014; Ma et al., 2020). In a large study across seven European countries, participants stated that they believe urban smart farming would provide more comfort for farmers and is useful for the agricultural sector in general (Knierim et al., 2018). The aspect of sustainability of urban agriculture was perceived as relevant in the Global North, hence countries such as Germany or the United States (Campbell & Rampold, 2021; Jürkenbeck et al., 2019), whereas social and economic factors played a larger role for people living in the Global South (Abegunde et al., 2019; Chimbwanda, 2016). The number of studies assessing perceived benefits of urban smart farming in the Global South is small. A recent study in 18 sub-Saharan countries showed that smart farming technology does not only have a direct positive effect on agriculture but also a positive impact on financial development and reduced energy consumption (Domguia & Asongu, 2022). Nevertheless, more research in this area (i.e., specifically on urban smart farming) could contribute to a more successful uptake of this technology in countries where the need for alternative solutions to conventional agriculture is critical (Audate et al., 2019; Gallaher, 2017). When it comes to demographic profiles, people who see urban agriculture positively are most likely older females with children (Murage et al., 2015).

Perceived barriers to engage in urban smart farming

Urban farming and urban smart farming are not perceived solely positive. Negative associations and worries connected to urban farming mentioned in the literature are, for example, perceived conflicts and competition with traditional ways of farming and traditional farmers (Specht & Sanyé-Mengual, 2017), the lack of knowledge about correct techniques and appropriate crops (Gumisiriza, Kabirizi et al., 2022; Klerkx et al., 2019) the risk of crop theft and the risk of diseases due to the location within the urban environment (Grebitus et al., 2017). Another large concern is responsibility diffusion (Regan et al., 2018), meaning that community projects rely on collective engagement and are therefore in danger of everyone assuming that someone else will take care of it. This is closely related to a lack of trust between community members (Jakku et al., 2019), especially in countries with high crime records. Further concerns are doubts about the availability of enough water and seeds for urban farming (Chimbwanda, 2016; Kernecker et al., 2020). Another point that is repeatedly raised was the question of beneficiaries (i.e., who will benefit and to what extent?; Klerkx et al., 2019) and a lack of sufficient funding for innovations in the agricultural sector (Gumisiriza, Ndakidemi et al., 2022). When it comes to urban smart farming in specific, typical perceived barriers are concerns about data ownership and sharing, a need for technology-specific training and a lack of technological equipment (Klerkx et al., 2019). Knierim et al. (2018) further found that their participants were worried about the day-to-day handling of the data and the usability of existing platforms for communication between contributing farmers. However, the perceived barriers about urban smart farming are not researched as thoroughly as for urban farming in general. This might be due to urban smart farms still being a relatively recent phenomenon.

As suggested by Provó et al. (2016) specific, local context of each urban agriculture project needs to be considered before implementation. This includes population-specific farming traditions, cultural values, demographic profiles and environmental conditions that can influence the acceptance of urban smart farming projects (Musa & Basir, 2021).

Methods and materials

Articles have been identified using PubMed, Scopus and Google Scholar that discuss perceived barriers and drivers for urban farming as well as urban smart farming. The influential factors identified in the literature were formulated into 12 drivers and 10 barriers (see Figure 1). For details on the literature review, please see Table S6. A short explanation ("urban smart farming is a concept that uses indoor, innovative technologies for community-led food production in idle buildings based on the circular economy principles, hence eliminating waste and the continual use of resources") was provided to ensure that respondents are familiar with the concept of urban smart farming. The intentions to get involved in urban smart farming projects were conceptualized as a latent variable consisting of five items ranging from relatively easy behavioral intentions such as communicating about urban smart farming projects to relatively difficult behavioral intentions such as leading and managing urban smart farming projects. Each driver and each barrier were represented by one item. Intentions, drivers and barriers were assessed on a five-point Likert scale, a convenient, easy and straightforward way to collect responses (Jebb et al., 2021). In addition, key demographics such as age, gender, education and income were included. In addition, previous familiarity with the concept of urban smart farming was assessed. The full survey can be found in the supplementary material (pp. 17–21). The survey was conducted in English, and a pilot questionnaire was conducted and completed by a subsample of N = 19 individuals (seven from South Africa, eight from Nigeria and four from Zambia).

Sample

The rationale behind the choice of the case study's countries was to represent differently geographically situated countries in sub-Saharan Africa, Zambia (eastern Africa), Nigeria (western Africa), South Africa (southern Africa). To the best of our knowledge, urban smart farming has not been implemented yet in these countries. Since urban smart farming is generically an urban phenomenon, the participants were recruited from urban areas. The appropriate sample size for multiple regression and a power of 80% were determined by the rule of thumb $N > 104$ + number of predictors by (Green, 1991; Van Voorhis & Morgan, 2007). Combining the twelve drivers, the ten barriers and the four demographic predictors yielded a minimum sample size of N = 130 per country. In total, N = 431 participants filled out the questionnaire. Seventeen were removed due to residency outside South Africa, Nigeria and Zambia or substantially missing data, giving a final sample of N = 414. All countries fulfilled the necessary sample size minimum of N = 130. The demographic characteristics of the participants are presented in Table 1.

Data collection procedure

The data collection in each country was led by the respective country partners. This study was conducted just as COVID-19 cases were spreading across the world and especially in Sub-Saharan Africa. To collect data, the surveys have been sent out to pools of potential respondents via e-mail and WhatsApp with a chain-referral sampling technique. This method was chosen due to the COVID-19 pandemic and the movement restrictions at the time. It allowed for data collection while minimizing face-to-face contact and ensuring the safety of the researchers and respondents. Further, chain-referral sampling in general has the advantage of reaching hidden populations (Bagheri & Saadati, 2015), providing more diverse and larger samples. Additionally, it allowed respondents to be able to complete the survey on their own devices, which further decreased risks for health and safety. All respondents agreed to information about their voluntary participation and data protection before responding to the survey questions.

Measures

A table of the items and the mean scores across all countries and country-wise can be found in Table S1.

Table 1. Sample characteristics, total and country-wise.

Variable		Nigeria	South Africa	Zambia	Total
Country		130 (31%)	148 (36%)	136 (33%)	414
Age (in years)	18–29	34 (26%)	40 (27%)	37 (27%)	111 (27%)
	30–39	55 (42%)	53 (36%)	40 (30%)	148 (36%)
	40–49	17 (13%)	28 (19%)	35 (26%)	80 (19%)
	50–59	23 (18%)	22 (15%)	22 (16%)	67 (16%)
	60–69	1 (1%)	3 (2%)	2 (1%)	6 (1%)
	> 70	0 (0%)	2 (1%)	0 (0%)	2 (1%)
Gender	Female	56 (43%)	61 (41%)	55 (43%)	175 (42%)
	Male	74 (57%)	87 (59%)	78 (57%)	239 (58%)
Education	Postgraduate	31 (24%)	49 (33%)	49 (36%)	129 (31%)
	Undergraduate	71 (55%)	72 (49%)	69 (51%)	212 (51%)
	Secondary	28 (22%)	27 (18%)	18 (13%)	73 (18%)
Income	Low	33 (25%)	31 (21%)	29 (25%)	96 (23%)
	Middle	80 (62%)	103 (70%)	78 (66%)	276 (67%)
	High	17 (13%)	14 (9%)	11 (9%)	42 (10%)

Dependent variable(s): Intentions to engage in urban smart farming

The intention scale consisted of five items (e.g., "If an urban smart farm project is initiated in my community, I will actively participate in it"), which were to be answered on a 5-point Likert scale (1 = completely disagree, 2 = rather disagree, 3 = undecided, 4 = rather agree, 5 = completely agree). Cronbach's alpha across all five intention items was high with $\alpha = .88$. To integrate the intention into the multiple regression, an index value for every participant was calculated, by calculating the sum score over each of the intention items and dividing it by the number of the items (Field et al., 2012).

Independent variables: Drivers and barriers to engage in urban smart farming projects

Twenty-two items (e.g., "Urban smart farming supports our community's health" [Community health]) were formulated, so they could be answered on a 5-point Likert scale (1 = completely disagree, 2 = rather disagree, 3 = undecided, 4 = rather agree, 5 = completely agree). A list of all items can be found in Table S2.

Analysis approach

The factors that significantly influenced the intention to engage with urban smart farming were tested using stepwise multiple regression. Analysis was conducted in RStudio (version 1.4.1106) and Microsoft Excel (version 16.58). R-packages used were analogue (Simpson & Oksanen, 2021), broom (Robinson et al., 2022), car (Fox & Weisberg, 2019), describedata (McGowan, 2019), Hmisc (Harrell, 2021), huxtable (Hugh-Jones, 2021), jtools (Long, 2020), olsrr (Hebbali, 2020), psych (Revelle, 2021), tableone (Yoshida & Bartel, 2021), tidyverse (Wickham et al., 2019) and xtable (Dahl et al., 2019).

Data was tested for suitability for linear regression analyses. Due to a left skew of the dependent measure, heteroscedasticity and non-normal residual distribution, the intention scale was linearly transformed with the common log as suggested by West (2021). Further, all independent variables were transformed likewise, to facilitate interpretation. Thus, slope parameter estimates can be interpreted as the percentage increase in the dependent variable per 1% increase in the independent variable. This approach is recommended to facilitate best parameter estimation (Benoit, 2011). The demographic variables were dummy coded and included as covariates in the regression models (Field et al., 2012). Country-wise correlation matrices for all predictors (Figure S1–S3) created with function provided by Laken (2020) and regression assumption tests (supplementary material pp. 5–6) can be found in the supplementary material.

Data limitations

Participants showed a tendency to answer at the higher end of the scale for most items, resulting in a strong ceiling effect for most of the driver and barrier variables as well as all items included in the intentions scale. Whilst the response variance in these items is still big enough to proceed with our analyses, it is important to consider this response tendency when making conclusions based on this data. Ceiling effects are often observed in Likert scale studies, particularly with untrained respondents.

It was investigated whether an overall multilevel model is suitable for the analysis of the present data set, with the individual respondents being nested in the three countries. However, the intraclass correlation was found to be very close to zero, meaning that there was a non-sufficient variance between the clusters (i.e., countries) for a stable multilevel estimation (Merlo et al., 2005). We recommend applying measures to reduce ceiling effects and allow for multi-level analysis to enable cross-country inference in future studies such as an increased number of response options or labeled response scale points (Chyung et al., 2020).

The decision to present country-specific instead of overall models for the perceived drivers and barriers is based on the aim to emphasize that the differences between countries are larger than their communalities. We do not want to promote a one-fits-all approach and see it as pretentious to lump countries together. Therefore, we decided to use three separate models, even though this means that the models can only be compared descriptively.

Results

An overview over all individual result patterns in Nigeria, South Africa and Zambia can be obtained in Figure 2 and will be presented country-wise below.

Nigeria

The overall model for Nigeria was significant $F(9,120) = 33.4$, $p < .001$ (see Figure 2). Overall, the model was able to account for 69% of the variance ($R^2_{adj.} = .69$). No demographic factors returned as significant predictors (see Table S3).

Drivers

In Nigeria, the feeling that urban smart farming would increase food security ($\beta = 0.39$, $SE = 0.11$) well-being of the community ($\beta = 0.90$, $SE = 0.17$) and opportunities for educational development ($\beta = 0.33$, $SE = 0.16$) were the significant drivers for the intention to engage in urban smart farming ($p < .05$). For example, this means that for every 1% increase in the feeling that urban smart farming

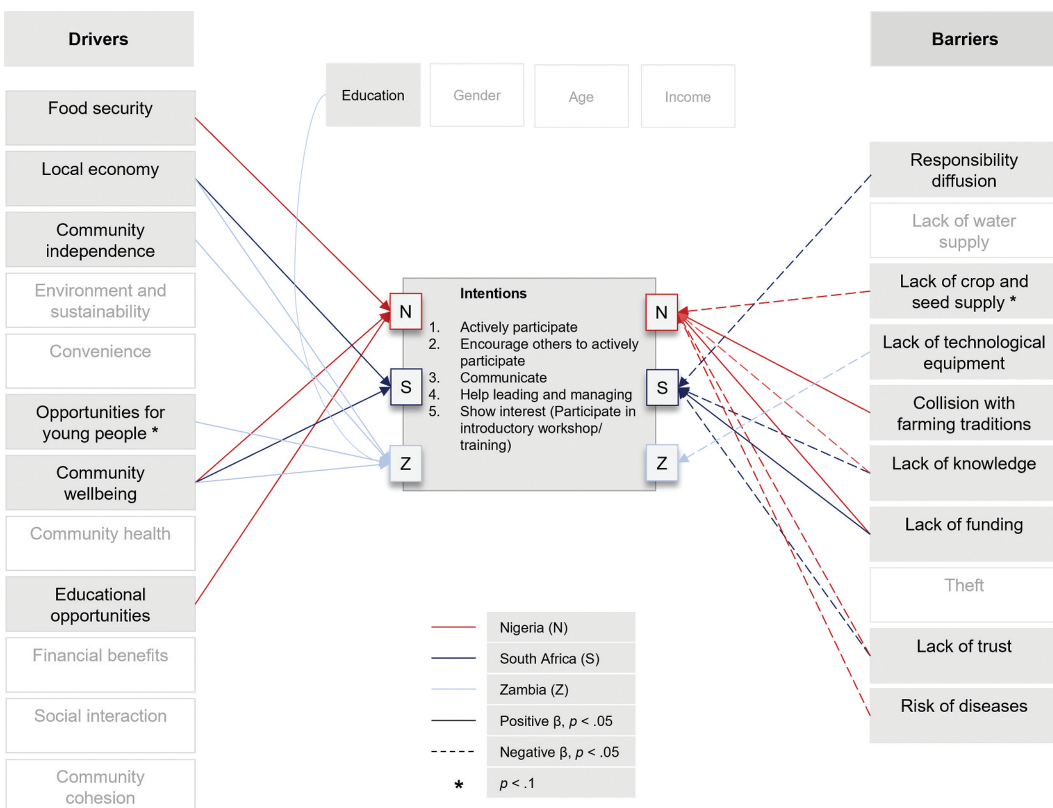

Figure 2. Significant drivers and barriers for urban smart farming projects in Nigeria, South Africa and Zambia.

could increase food security the intention to engage in it increases around 0.39%. In other words, for every 40% increase in the independent variable, the dependent variable increases about 14.3%.

Barriers

In turn, the lack of trust in other collaborators (β = −0.38, *SE* = 0.12), risk of diseases spreading due to urban smart farming (β = −0.34, *SE* = 0.14) and lack of topic-specific knowledge (β = −0.24, *SE* = 0.12) significantly reduced the intention to engage in urban smart farming ($p < .05$). Further, the concern about lacking necessary crops and seeds (β = −0.39, *SE* = 0.11) was a marginally significant barrier ($p < .1$). This means that for every 1% increase in the lack of trust the intention to engage in urban smart farming decreases around 0.38%. The concerns that urban smart farming could collide with local farming traditions (β = 0.40, *SE* = 0.12) and that urban smart farming could lack in funding (β = 0.40, *SE* = 0.11) were significant positive predictors for the intention to engage in urban smart farming, meaning that the more an individual agreed with collision with farming traditions and lack of funding the less they intended to engage in urban smart farming projects (see discussion).

South Africa

The overall model for South Africa was significant $F(6,141) = 28.7$, $p < .001$ (see Figure 2). Overall, the model was able to account for 53% of the variance ($R^2_{adj.} = .53$). No demographic factors returned as significant predictors (see Table S4).

Drivers

In South Africa, the feeling that the local economy (β = 0.31, *SE* = 0.13) and the well-being of the community (β = 0.89, *SE* = 0.16) could benefit urban smart farming projects positively influenced the intention to engage in urban smart farming ($p < .05$). For the local economy, for example, this means for every 1% increase in the independent variable the intention to engage in urban smart farming increases around 0.31%.

Barriers

In turn, the concern that no one will take the reins for such a project, i.e., responsibility diffusion (β = −.35, *SE* = 0.15), the lack of trust in other collaborators (β = −.58, *SE* = 0.12) and lack of topic-specific knowledge (β = −.32, *SE* = 0.12), turned out to significantly inhibit the intention to engage in urban smart farming projects ($p < .05$). For example, this means that for every 1% increase in the concern of responsibility diffusion the intention to engage in urban smart farming decreases around 0.35%. Similar to the pattern to Nigeria, the feeling that a lack of funding could pose a threat to urban smart farming projects (β = .62, *SE* = 0.11, $p < .05$) was a barrier associated with a more positive intention (see discussion).

Zambia

The overall model for Zambia was significant $F(7,128) = 19.64$, $p < .001$ (see Figure 2). The model was able to account for 49% of the variance ($R^2_{adj.} = .49$). As a demographic factor, education turned out to significantly predict the intention to engage in urban smart farming projects (see Table S5). Specifically, participants with secondary/high school education were associated with less self-reported intention (β = −0.18, *SE* = 0.08, $p < .05$), compared to the reference group (postgraduate). It is, however, important to note that this model did only marginally significantly outperform the model without any demographic factors on the 5% level, $F(2,128) = 2.95$, $p = .06$.

Drivers

In Zambia, the feeling that the well-being (β = 0.28, *SE* = 0.17) and the independence (β = 0.32, *SE* = 0.1) of the community could profit from urban smart farming projects, as well as an increase in opportunities for young people (β = 0.79, *SE* = 0.21) turned out to be significant drivers for the intention to engage in urban smart farming ($p < .05$). Further, hoping that urban smart farming would positively influence the local economy was a marginally significant driver (β = 0.28, *SE* = 0.17, $p < .1$). This means that for every 1% increase in the independent variable community well-being the intention to engage in urban smart farming increases around 0.28%.

Barriers

In turn, the concern about lacking necessary technological equipment (β = −0.29, *SE* = 0.11) was a significant barrier, i.e., decreased the intention. For every 1% increase in the independent variable lack of technological equipment the intention decreases around 0.29%.

Discussion

The aim of this study was to explore people's general intentions to engage in urban smart farming in three African countries and to understand perceived drivers and barriers of this intention to engage with this novel technology in each country.

Urban smart farming projects were perceived favorably by the respondents, reflected by relatively high mean values in all five items reflecting behavioral intentions to engage in urban smart farming projects. Similar patterns have been reported by Zhou et al. (2022) with Chinese participants or by Canavari et al. (2022) who showed high acceptance and demand for a sustainable urban smart farming technology. In our data, two items stood out: the intentions to actively participate in an urban smart farm project as well as the intentions to be involved in the project management have been found to be highest of all intention items across the three countries. The intentions to talk about urban smart farming were relatively low indicating that the sample prefers to take actual steps toward implementing urban smart farming in their community instead of only talking about the idea. Respondents from South Africa and Zambia show particularly high intentions to participate in an introductory workshop or training about urban smart farming, indicating an eagerness to learn about this new technology. All items have been responded to at the upper end of the scale resulting in a tendency toward a ceiling effect. This could either indicate a problem with the response scale or simply represent a very strong overall intention in the sample to implement urban smart farming projects in their communities.

The country-specific model for Nigeria indicates that community well-being is the most important driver affecting urban smart farming intentions, similar to findings by Othman et al. (2018) showing that social and health benefits are the highest motivating factors for urban farmers in Malaysia. A study conducted by Schukat and Heise (2021) also finds social influence to be a strong force driving behavioral intention to adapt smart products in farming practices in Germany (see also Canavari et al. (2021)). Educational opportunities and food security significantly predict intentions to engage in urban smart farming in Nigeria as well, albeit not as strong as community well-being. Similar to our results, a study by Home and Vieli (2020) found that socialization and food production are the strongest motivational forces behind urban gardening in Switzerland and Chile. This study also found that restoration, a variable not assessed in our study was a strong predictor for urban gardening motivation. The emphasis urban smart farming puts on the use of more inclusive and fair practices as compared to conventional agriculture is in line with the aim to move toward "zero hunger" in Nigeria (Tajudeen & Taiwo, 2018). Conventional agriculture in Nigeria is known for heavy use of chemicals, pesticides and harmful irrigation techniques which does not only harm the environment but also endangers food security in the long run (Healy & Rosenberg, 2013). In the regression model for Nigeria, a variety of barriers for the engagement in urban smart farming projects have been identified with a lack of trust as the strongest barrier, followed by the risk of diseases, a lack of knowledge and a lack of crops and seeds, albeit the last barrier is only marginally significant. According to Nwozor et al. (2019), people in Nigeria feel increasingly unsafe in their country, leading to a lack of mutual trust and collaboration. This might affect their confidence in starting new methods such as urban smart farming where intense collaboration is required and at the same time a longing for community well-being as mentioned before. The lack of knowledge about modern agricultural practices is also discussed on a national level when it comes to future strategies for the agricultural sector (Elugadebo, 2016). Collision with farming traditions had a non-intuitive, positive relationship with the intention to engage in urban smart farming in Nigeria. In other words, the more urban smart farming is perceived to be different from traditional ways of farming, the more people support it. A reason for this might be that conflicts between Fulani herdsmen and farmers are increasingly escalating, resulting in high numbers of deaths, making traditional farming dangerous (Dewan, 2022). Farmers are facing displacement from their farmlands through Fulani herdsmen and thereby the loss of their major source of livelihood. Smart farming in urban environments might seem a safer option for traditional farmers facing the current threats. Another non-intuitive finding is that the less funding for agriculture is available, the more people feel that they want to engage in urban smart farming, potentially as an alternative. In contrast, other studies have demonstrated that this factor can pose a substantial obstacle to the adoption of smart farms, as it was the case in a Korean study (Yoon et al., 2020). Nevertheless, this pattern might be connected to two core problems of Nigerian agriculture, the lack of good quality seeds and crops for traditional agriculture (Ajibefun, 2018) as well as the recent transition toward the oil sector as major economic driving force of the country, leaving the agricultural sector struggling for financial capital (Nwozor et al., 2019). Furthermore, the research conducted by Yoon et al. (2020) centers around the implementation of non-urban smart farming, specifically within established farming companies, highlighting the inherent riskiness of making significant investments in such endeavors. In contrast, it seems like our respondents from Nigeria see urban smart farming as a solution to break with financial and intergroup struggles by focusing on different, easier available crops and less resource-intensive methods. Requiring little financial resources, space, water, soil and maintenance, urban smart farming seems to be an attractive alternative for many.

Similar to Nigeria, community well-being is the strongest driver of intentions to engage in urban smart farming projects in South Africa, followed by perceived advantages for the local economy. This is in line with findings by Bisaga et al. (2019), Moghayedi et al. (2022) and Zainal et al. (2020), also indicating that the adoption of technological innovations is mostly driven by factors connected to community well-being and the economy. The most important barrier in South Africa is a lack of funding for agriculture, which increases the willingness to engage in urban smart farming. Once again, the somewhat counterintuitive finding, which is also in contrast to the study conducted by Yoon et al. (2020), can potentially be elucidated by considering the local context. The reason could be that people perceive urban smart farming to reduce the reliance on subsidies for agriculture or cash for food supplies and allows people to independently provide their family with basic necessities (Ackerman et al., 2014). Urban smart farming can be a solution to generate additional income and nutrition. Lack of trust is another perceived barrier in South Africa, which might be rooted in the long history and the background of Apartheid in the country, blocking trustful collaboration between different actors and perspectives, which would be necessary to start a new economic sector such as urban smart farming (Vogel et al., 2016). Furthermore, a lack of knowledge seems to hamper the intention to engage in urban smart farming projects, in line with Chitakira and Ngcobo (2021) also pointing to a lack of knowledge on implementation level. Bisaga et al. (2019) describe that knowledge gaps related to urban farming are prevalent in low-income settlements, areas where self-sustaining activities would be particularly helpful. A potential solution here could be local-level workshops and community capacity building to increase not only knowledge but also the image of urban smart farming projects and reduce anxiety (see Canavari et al., 2021). Then, the last significant barrier in South Africa is responsibility diffusion, something that might have its roots in the abolition of apartheid and the transition to a democratic distribution of land in South Africa. Even though the South African government is supporting the rise of corporate social responsibility, there are no existing guidelines of which responsibilities are to be taken by whom, resulting in complications and confusion as well as an overall reluctance to lead businesses, especially in the agricultural sector (Kloppers & Fourie, 2014). Furthermore, this variable holds significant importance in the context of smart farming implementations, where the primary focus tends to be on individual farms with clearly defined responsibilities (e.g., Schukat & Heise, 2021). As a result, this variable is often overlooked and not extensively studied. However, urban smart farming largely involves community-based approaches, resulting in less clearly defined responsibilities. Consequently, it appears reasonable to establish and structurally support defined responsibilities to effectively facilitate and solidify the community-based approach in urban smart farming initiatives. Beyond our study, recent publications have also identified other personal factors that could limit the use of urban agriculture in South Africa. In a study in Cape Town, Kanosvamhira and Tevera (2021) identified lack of time and large distances between the urban agriculture projects and potential users as limiting factors.

Whilst Nigeria and South Africa appear to have partly similar perceptual profiles, participants from Zambia mainly report different drivers and barriers for urban smart farming to be most important for behavioral intentions. Opportunities for young people are the most important driver to engage in urban smart farming for participants from Zambia. This could be rooted in the country's relatively poor economic performance, providing little hope for the young generation. While South Africa and Nigeria occupy the first and second rank in economic performance in Africa (measured in GDP), Zambia stands low on the list, at rank 20 (Kramer, 2022). This makes opportunities for occupation and education more relevant in Zambia than in Nigeria and South Africa. Further, community well-being was found to be an important driver together with community independence. Community well-being and independence are closely linked to small-scale urban agriculture (Voleníková & Opršal, 2016) especially as it provides an independent source of food in a country that has a long history of food shortages (Mulumbi, 2015). Perceived support for the local economy was also identified as a slightly weaker driver for behavioural intentions in Zambia, which is most likely also connected to the poor economic performance of the country leading to people struggling for subsistence. Urban smart farming can also have positive spillover effects due to small job opportunities and cooperation between people (Voleníková & Opršal, 2016). The most important barrier for the intentions to engage in urban smart farming in Zambia was a lack of technological equipment, which is quite intuitive for a country where there is low technological input and thus a lack of use of specific technologies (Silva et al., 2023). A lack of technological equipment was also recently found to be an important barrier for the adaption of climate-smart agriculture in Zambia (Khoza et al., 2022). No other barrier could be identified in Zambia pointing toward a general willingness and motivation to engage in the new method if technological equipment is provided. Zambia was also the only country in which the level of education was significantly related to different levels of behavioral intentions. Participants with higher levels of education such as high school seemed to have higher intentions to engage in urban smart farming than participants with lower levels of education. This is in line with Khoza et al. (2019) who also find educational levels in Zambia as being the main barrier to the adoption of climate smart agricultural techniques.

In previous studies, demographic profiles characterized by people's age, gender, education and income group have been mentioned as relevant criteria for the acceptance of urban (smart) farming projects and the engagement (Abegunde et al., 2019; Caffaro & Cavallo, 2019; Canavari et al., 2022; Ma et al., 2020; Murage et al., 2015; Provė et al., 2016; Sanyé-Mengual et al., 2018). The study conducted by Schukat and Heise (2021) found that the age of respondents influenced the impact of technology readiness, which refers to an individual's willingness to personally evaluate technological advancements as beneficial, on behavioral intentions. Notably, this effect was weaker for older participants. In general, younger individuals tend to be more receptive to new technologies, whereas old age often is a hindering factor thereof (Canavari et al., 2022; Van Volkom et al., 2013). Nevertheless, in terms of farming, this is most likely linked to education advantages of the younger population rather than age per se (Lissaman et al., 2013). In the current study, in contrast to the studies cited, demographic profiles of people did not emerge as influential for our participant's intentions as compared with people's perceptions of drivers and barriers for the engagement in urban smart farming projects. One exception here is the level of education that seems to play a role in predicting intentions in Zambia. Even here, the predictive power does not add significantly to the regression model indicating that people's perceptions about benefits and disadvantages of urban smart farming are more important to explain their intentions. A similar finding has been observed by Hartley et al. (2018) in a European-wide study investigating people's intentions to engage in solutions for plastic pollution where perceptions of severity of the problem or perceptions around other people's behavior have been found to be more productive than demographics such as the participant's age or gender. These patterns could point toward the importance of considering psychological variables and perceptual profiles when creating interventions and communication approaches in addition to the traditional approach of considering solely sociodemographic profiles (Dolnicar et al., 2018).

Implications for practitioners and policy

Our findings may assist both policymakers and practitioners to understand and potentially enhance people's intention to engage in urban smart farming projects. The core lesson learned is the importance of people's perceptions about urban smart farming and the necessity to adapt communication, respectively. We further underline that any intervention, communication or policy needs to be aligned with local circumstances on a country or even regional level. Evidence from environmental communication research advises against the provision of generalized information or one-fits-all approaches and emphasizes to get to know the target audience and to tailor the communication to address people's perceptions, worries and hopes (Moser, 2010; Moser & Dilling, 2006; Oyero et al., 2018). This recommendation is backed up by our study as each country displays a different pattern of predictors.

The exceptionally high level of overall intention to engage in urban smart farming projects in all three countries, Nigeria, South Africa and Zambia might indicate that efforts to *motivate* communities to join in urban smart farming initiatives will most likely not be necessary due to the motivation being high already. Indeed, a high behavioral intention to engage in smart farming has proven to strongly predict the adaptation of smart technology in farming (Schukat & Heise, 2021). Instead, efforts and funds can be utilized to help transforming this motivation into action. For this, we suggest minimizing the concerns about perceived country-specific barriers such as a lack of knowledge or technological equipment through strategic training, targeted support measures (e.g., providing the missing equipment) and localized funds. Delivering comprehensive guidance, in terms of tools and knowledge, for the integration of urban agriculture has emerged as a pivotal determinant in fostering participation within such initiatives (see also Alemu & Grebitus, 2020; Yoon et al., 2020). Considering that inadequate knowledge was identified as a notable hindrance in two of the examined nations, specifically South Africa and Nigeria, it becomes imperative to offer sufficient and pertinent instruction throughout the execution of urban smart farming endeavors. Conversely, in Zambia, where knowledge deficiency was not a prominent obstacle, but scarcity of equipment was, equipping communities with appropriate technology and imparting utilization knowledge assumes significance. Furthermore, through the enhancement of knowledge and cultivation of confidence in the utilized technologies, it becomes plausible to reinforce trust in urban smart farming projects. This aspect is also a noteworthy hurdle in South Africa and Nigeria to overcome, and trust has been found to be linked with heightened intentions to participate in urban smart projects (Schukat & Heise, 2021). Furthermore, this endeavor can not only contribute to the already high intentions in all three countries but also enhance the image of urban smart farming, alleviate anxiety and increase the self-efficacy of participants. The first variable has been observed to positively impact the perceived usefulness, which subsequently directly influences behavioral intentions. The latter two variables, on the other hand, are influential in shaping the perception of ease of use of smart technologies (Canavari et al., 2021). The aspect of perceived usefulness in general is an important driver for behavior intention; hence, in line with Moghayedi et al. (2022), we finally also recommend emphasizing perceived benefits.

Community well-being stands out as particularly important perceived driver across countries which should therefore be the main focus of communication approaches, already recommended by Sanyé-Mengual et al. (2018). Facets of this community well-being that could be promoted are independent subsistence, mutual appreciation, friendships, quality of life and an expanding sharing culture, for example (Franck, 2005; Voleníková & Opršal, 2016). Explicitly communicating the opportunities of urban smart farming on a local level can help to strengthen the perceived benefits and thereby actively engage communities. Country-specific nuances and concerns need to be considered in this communication, such as the history of diseases and lack of crops and seeds in Nigeria, fear of responsibility diffusion and low levels of mutual trust between community members in South Africa or severe economic struggles in Zambia.

Conclusion

In this study, we investigated the perceived drivers and barriers regarding novel and innovative approaches to agriculture (i.e., urban smart farming) of potential users. To the best of the authors' knowledge, this is the first study that has emphasized the user perspective on urban smart farming in Africa. We found that general intentions across all three countries are very high, albeit predicted by different patterns of perceived drivers and barriers. People living in Nigeria and South Africa seem to perceive urban smart farming in a relatively similar way, with a lack of knowledge and trust being shared barriers. Interestingly, lack of funding was a positive predictor in both countries, possibly due to the economic opportunities seen in urban smart farming. In Namibia, food security and opportunities for young people strongly positively influenced the intention to engage in urban smart farming and the fear of diseases had a negative influence, while South Africa was the only country in which responsibility diffusion was a significant barrier. Zambia stands out with a unique pattern of perceived drivers and barriers, with most drivers closely related to communal benefits (community independence, opportunities for young people, educational opportunities and local economy) and only lack of technological equipment was seen as a barrier. Overall, the perception that community well-being could benefit from urban smart farming was the only driver or barrier whose significance was shared by all three countries, which is in line with recent studies (Atmaja et al., 2021). Establishing urban smart farming projects to strengthen community well-being is therefore one of the most promising ways to get people involved across countries. An engaged community that perceives community benefits will also enjoy the objective benefits of urban agriculture, such as food security and the creation of new educational and economic opportunities, which in turn might further increase the perception of community well-being. Finally, we would like to point to the importance of considering local circumstances and perceptions when designing interventions for them to be most appropriate and effective. For future studies, we recommend putting our findings into practice and testing the effects of tailored communication approaches that consider perceived drivers and barriers to engage in urban smart farming.

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We confirm that all authors contributed to the development and finalization of the submitted manuscript. **IR** and **NN** equally contributed to the manuscript resulting in shared first authorship. Specifically, **IR** was responsible for conceptualization, methodology, survey design, writing, original draft and supervision. **NN** was responsible for data analysis and presentation, visualization and writing—reviewing and editing. **AM** is the project lead. **AM, MO, KK, SF** and **EK** contributed to the data collection as well as writing—reviewing and editing.

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