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A Bayesian Inference Model for Sustainable Crowd Source Logistics for Small and Medium Scale Enterprises (SME) in Africa

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Abstract

Trade in Africa is likely to increase and alter significantly during the next decade. Intra-African trade has shown significant potential to reinvigorate African commerce. Logistics and distribution are critical, acting as a catalyst for private sector development and growth. However, little attention has been given to the association crowd logistis platforms and SME's in Africa. This study applies an Extended Technology Acceptance Model (ETAM) to explore the implications of crowd-sourcing logistics for small and medium-sized enterprises (SMEs) in the African market. A survey was conducted to obtain the necessary primary data from 130 SME owners across Africa. To provide further insight, this study adopts a Bayesian inference model to analyze the data obtained. This research also considers perceived risk as an additional external factor of the TAM as a vehicle to test the hypotheses and relationships and explain users' willingness to adopt a web-based logistical platform. Empirical results show that in the adoption of new Technology; it is worth noting that for SME owners external factors (i.e. subjective norms, perceived risk, perceived experience) have more effect on the perceived usefulness of crowd logistics platforms than intrinsic factors (i.e. perceived enjoyment, computer anxiety and self efficacy).The analysis also showed that crowd logistics platforms provide a competitive advantage for SMEs but the perceived risks associated with crowd logistics platforms should be regulated.

Keywords

Crowd-logistics, Markov Chain Monte Carlo, Bayesian Statistics, Extended Technology Acceptance Model, Probabilistic Programming, Python

1. Introduction

The importance of small and medium-sized enterprises (SMEs) in emerging economies has been thoroughly documented in the literature (Muriithi, 2017). SMEs have been highlighted as a critical component of quick development, a thriving and rising economy. SMEs in Africa help to provide much-needed jobs, as well as providing sustainability and innovation for economic growth and development (Beck & Cull, 2014). According to data from the United Nations Economic Commission for Africa (UNECA, 2020), SMEs account for more than 90% of private firms and account for more than 50% of employment and GDP in the majority of African countries. In light of the above, the promotion of small and medium-sized enterprises (SMEs) has become fundamental to the development of most African economic growth policies.

Rethinking delivery and logistics services as the world recovers from COVID-19 is more crucial than ever before (Adenauer, 2021). With the advent of the internet and e-commerce, small and medium-sized firms (SMEs) now have an equal playing field to compete with well-established large corporations (Kafle et al., 2017). Increasing development potential comes more competition, particularly for SMEs still fighting to recover from the epidemic.

In Africa, SME's expansion has been undermined by rising logistics and delivery costs. In order to meet consumers' rising demand for shorter delivery time frames, Freight Shipments must be more frequent and smaller. This results in fewer than full truck loads and more empty trips, as well as greater demand for quick, energy-intensive modes of transportation (Huang et al., 2020). As a result, there has been a rise in air and noise pollution, congestion and traffic jams, as well as an imbalance in the demand and supply of truck parking space (Bosona, 2020). Parking charges and associated penalties cost most companies between $500 and $750 a week in order to offer consumers with prompt service and remain competitive (Parkopedia, 2019).

To guarantee long-term sustainability, it is imperative that SMEs embrace new and innovative delivery techniques (Alnaggar et al., 2019). In response to this, businesses have implemented a range of efforts including absorbing part of the delivery cost, setting up fully automated customer fulfillment centers, and innovative delivery routing techniques in a bid to provide timely deliveries and retain customers (Alnaggar et al., 2019).

One such systems is "crowd-sourced logistics", in which regular people or the crowd provide delivery services using their own means of transportation, such as bicycles and automobiles, from shops or warehouses to end consumer destinations (Lin et al., 2020). With the use of crowd-sourced transportation capacity, it is possible to complete deliveries without the need for specialist logistical services to be deployed. For SME's, this translates into lower delivery costs, more timely delivery, and less environmental impact (Mladenow et al., 2015).

The fundamental feature of this approach is that it enables people to share their underutilized property with companies and themselves in order to generate value for both parties (Devrani 2019; McLean, 2015). Though this model is not new, the advent of the digital economy, including the internet, mobile communication technology, and the global positioning system (GPS), has significantly expanded the scope for many actors to organize all forms of trades with speed and efficiency (Li & Liu, 2021). All of this presents SME's with untapped potential for sustainable green logistics to enable same-day delivery in a timely manner.

On the other side, Africa's ICT infrastructure has grown tremendously (Ismail, 2020), with current internet penetration in Africa being at 32.4 percent (Howe, 2015) as additional internet platforms are built daily. As more individuals utilize technology in their everyday lives, technological advances are gaining appeal across Africa. Despite the fact that these digital changes have been made, the issue of whether or not the African market would be open to crowd-logistics and the tools that are required remains unanswered.

Additionally, little attention has been devoted to the variables that encourage and restrict SME adoption of crowd logistics. Despite the fact that previous research has concentrated on identifying the primary drivers of crowd logistics, we know very little about the factors that facilitate the adoption of crowd logistics by small and medium-sized enterprises (SMEs). Huang et al. (2020) investigated the elements that impact crowd workers' desire to continue working in crowd logistics. To the best of our knowledge, no studies have been conducted in Africa that looks at crowd logistics from the standpoint of SMEs. Against the above background, research into crowd logistics and its adaptation by businesses with focus on SME's is imperative.

To address these research gaps, this study attempts to investigate the factors that influences acceptance of crowd logistics by SME owners. With regard to these difficulties, we focus on perceived ease of use and perceived usefulness as the two main factors that influence use of crowd-logistics platforms (Salman & Abd.Aziz, 2015). These factors have the ability to impact SME owners' choice to use crowd logistics. As a result, a survey-based sample of 130 African SME owners was analyzed to evaluate the suggested approach.

In addition to contributing to existing literature on crowd logistics, the findings of this study analyze the present condition of crowd source logistics in Africa, as well as the adaptation of SME's to the African market using crowd source logistics.

The rest of this research paper is organized as follows: in Section 2 we present an in-depth literature review with a detailed definition of Crowd logistics. Section 3 explains our applied research methodology. Subsequently, in Section 4, we present our results of the data analysis and discussions. This paper concludes with some concrete policy recommendations and future research direction.

2. Literature Review

2.1. Crowd Logistics

Crowd logistics is a significant and fast expanding subset of crowdsourcing (Mladenow et al., 2015). Howe developed the phrase "crowd-sourcing" in 2006, defining it as outsourcing an activity usually performed by chosen agents such as employees to an unknown but considerable number of individuals through open recruiting (Howe, 2006). Crowdsourcing enables the public to do jobs that were previously performed solely by a few professionals (Huang et al., 2020). Crowdsourcing, when used properly, has the potential to benefit organizations of all sizes in a number of ways, including crowd-funding for capital, crowd-libraries, and crowd-clients for information sharing. Crowd-logistics is a new avenue for companies to provide value for their consumers at a lower cost (Mladenow et al., 2016).

Businesses have adopted crowd-logistics to implement logistical needs (Alnaggar et al., 2019); in 2015, Amazon launched a crowd-sourcing logistics service called *Amazon Flex*, which employs independent freelance drivers to deliver merchandise to clients along pre-planned routes. Amazon adopted *Amazon fresh* for time-sensitive items such as groceries, which guarantees a two-hour delivery window (Mehmann et al., 2015).

Additionally, Walmart began testing a crowd-sourcing logistics service called *Spark Delivery* in 2018; DHL also created *MyWays* to assist crowd-sourcing logistics by connecting end-consumers with the crowd (Kafle et al., 2017). For SME's in developed nations, there has been an exodus of courier crowd-sourcing delivery platforms like *DoorDash*, *Kanga*, *Roadie*, *PiggyBee*, *UberFreight*, *Truxx*, and *BuddyTruck*, which act as a critical connection between SME's and freelance drivers interested in delivering products for businesses (Alnaggar et al., 2021).

Research by (Mladenow et al., 2015) looked at the adoption of crowd logistics delivery platforms by business giants such as Amazon, Google, Wallmart, DHL and E-bay; they identified the need for disruptive business models, low cost structure and the immense power of the crowd as the reason for the rapid growth of crowd logistics platforms in developed economies. Focusing on the current growing industry of crowd logistics in the United States, (Alnaggar et al., 2021) reviewed different crowd sourced delivery platforms and concluded that crowd logistics platforms were here to stay and called for a more in-depth look at a variety mechanisms for its growth.

2.2. Motivation for the Adoption of Crowd Logistics by SMEs and Crowd

SME's are considering using crowd-logistics because of its enormous potential to drive business-related operations, reduce costs, and provide customer value (Lin et al., 2020). Indeed, scholars are increasingly examining the possible implications of crowd-logistics. According to Alnaggar et al. (2019), contemporary industry trends are evolving toward more sustainable sources of delivery and logistics; he noted the necessity for crowd-logistics platforms to use efficient scheduling and routing approaches in order to expand their value chain. Since bikers and pedestrians are increasingly being considered "crowds," it is commonly recognized (Kafle et al., 2017) that crowd-logistics, urban package delivery, and green logistics go hand in hand. SME's, for example, may circumvent the lack or difficulty of recruiting skilled logistics teams and delivery services by engaging crowd services to transport items along route to their destination (Lin et al., 2020). Additionally, SME's may promote their shared social responsibility by supporting green logistics, since crowd-logistics cuts emissions and pollutants produced by cargo vehicles by around 55% (Huang et al., 2020).

It is estimated that private vehicles and bikes are utilized by individuals less than 50% of the time (Li & Liu, 2021) leading to under-utilization of resources which could be otherwise used to generate income. As such various researchers have investigated how these underutilized resources could be used to create value for both businesses and owners of these resources (Buldeo Rai et al., 2017; Huo Bin, Feng Zhao, Guojie Xie, Lijuan Huang, HuanFang Wang, & Ruidong Zhu, 2020). But the adoption of crowd logistics platforms by both users and crowd has been shown to be reliant on a number of key issues. Research by (Alnaggar et al., 2021), shows that the allowed delivery time window, routing and monetary incentives were some key issues driving more users to adopt crowd logistics. However, this increase carries with it certain inconveniences for the suppliers of crowd services. According to Lin et al. (2020) packaging design, waiting time and route diversion are some key factors that inhibit the penetration of crowd-logistics. **Table 1** summarizes key studies on this subject.

Finally, researches have stated that crowd-logistics provides value to all stakeholders involved; it helps SME's to access a larger market and better customer interactions while also generating cash from otherwise underutilized resources for the community participating (Gong et al., 2021).

In Africa there exists a huge gap of limited available crowd logistics platforms

Table 1. Theories that drive crowd logistics for businesses and crowd.

Source	Method	Key Findings
Bosona, 2020	Systematic Literature Review	Urbanization, Population growth, densification, globalization, urban economic development
Huang et al., 2020	Push and Pull Mooring Theory	Previous job flexibility, Trust, Cost of participation, Monetary rewards
Mladenow, Bauer and Strauss, 2015	Social Crowd	Monetary rewards, trust and psychological factors
Buldeo Rai et al., 2017	Systematic Literature Review and Semi-structured Interview	Technological Infrastructure, Free Capacity, Crowd Network
Mehmann, Frehe and Teuteberg, 2015	Systematic Literature Review and Qualitative Data Analysis	Cooperation, Economy, Revenue, payment, Billing, Communication and Access
Zhang et al., 2019	Organization Information Processing Theory	Logistics platform agility and Logistics resource-demand match
Mofidi and Pazour, 2019	Bi-level Optimization and Computational Study	Information Transparency and availability of choices can drive crowd logistics
Alnaggar, Gzara and Bookbinder, 2021	Systematic Literature Review	Delivery time window, routing, scheduling and payment
Lin, Nishiki and Tavasszy, 2020	Case study of Cyclists in Netherlands	Route selection, parcel design and waiting time.

for businesses. As shown by our review, little attention to date has been given to the question of whether the African market is amenable to crowd-logistics and the associated instruments. As per (Denis Benoit, 2021), it is clear that the digital economy in Africa is growing quickly and will soon become a major force in global economic growth as a whole. In recent times, more people are incorporating technology into their daily lives and technological advancements are gaining popularity throughout Africa (Azmeh & Foster, 2018). As such, studying the factors that affect the adoption of crowd-logistics by the African market has significance as Africa possess a huge market potential for crowd logistics platform.

Additionally, existing research focuses mostly on crowd-logistics for big firms and e-commerce, with little or no attention on SMEs and their usage of crowd-logistics. As a result, this article tackles the aforementioned two gaps by adapting TAM to evaluate the link between SMEs and crowd-logistics and then testing the model in the African environment.

2.3. Technology Acceptance Model (TAM)

The Technology Acceptability Model (TAM), established by Davis in 1989 (Davis et al., 1989), can forecast the acceptance and utilization of Crowd-logistics platforms. Although various theories, such as the Theory of planned behavior (TPB) (Ajzen, 1991) have been developed to examine and forecast system acceptance, the TAM model is the most frequently recognized model because it is seen to be more parsimonious, predictive, and resilient than the other models. Various academics in the field of information systems have used it to examine the effect (Liao et al., 2018; Salman & Abd.Aziz, 2015).

TAM is a collection of external variables that track the influence of external factors on two major user perceptions: Perceived Ease of Use (PEOU) and Perceived Usefulness (PU) (PU). These perceptions influence users' favorable or negative attitudes toward technology. One's attitude about utilizing technology effects one's behavioral intention to use and, ultimately, defines the technology's actual use.

2.4. Model of Extended Technology Acceptance Model

The most essential variables in the technology adoption model are perceived ease of use and perceived usefulness. Perceived Ease of Use is defined as "the degree to which a person feels that utilizing a certain system would be devoid of effort." The definition of perceived usefulness is "the degree to which a person feels that employing a certain system will improve his or her performance." Both of these characteristics are impacted by external influences in the TAM model. As a result, including these external elements in the TMA model is critical for describing technology adoption behavior (Davis et al., 1989).

Additionally, Davis et al. (1989) contended that TAM without external factors provides only general information about users' perceptions of a system and does not provide particular information that may help drive system development.

TAM with defined external factors not only forecasts technology utilization but also explains why a specific system may be accepted, allowing researchers and practitioners to take suitable corrective measures (Davis, 1989).

As a result, several studies have expanded TAM with other external components to support a range of issues (Abdullah & Ward, 2016; Sorce & Issa, 2021). Researchers that study the extension of TAM are primarily concerned with the interactions between external influences and the two core dimensions of TAM (PEOU and PU). This research adopts the TAM model as discussed by (Davis et al., 1989) and is presented in **Figure 1** below.

2.5. Self-Efficacy

Self-Efficacy is the first external component evaluated in TAM in the context of crowd-logistics platform utilization. Self-Efficacy (SE) refers to an individual's judgment of his or her own capability to perform a specific task (Bandura, 1982). In the context of computer usage, "Computer Self-Efficacy" (CSE) refers to a person's confidence in his or her ability to complete a task with a computer (Karsten et al., 2012). CSE can affect people's behavioral intentions to use computers, because people who consider computers too complex and believe that they do not have the ability to use computers will avoid them (John, 2013; Karsten et al., 2012; Loar, 2018). In contrast, "the higher the individual's computer Self-Efficacy, the greater his/her usage of computers" (Teo et al., 2010). Research shows that SE has a significant impact on how a user perceives the usability of a new platform or technology (John, 2013; Karsten et al., 2012; Romero et al., 2009). This shows that SME owners with greater Self-Efficacy are more inclined to use crowd-logistics platforms (Romero et al., 2009; John, 2013), whereas SME owners with lower Self-Efficacy may avoid utilizing it.

2.5.1. Subjective Norm

Also, a person's "perception that the majority of individuals who are significant to him think he should or should not execute the conduct in question" (Hill, 1977) is defined as subject norm. With regards to crowd-logistics platforms social influence plays a key role towards decision making. For SME owners the

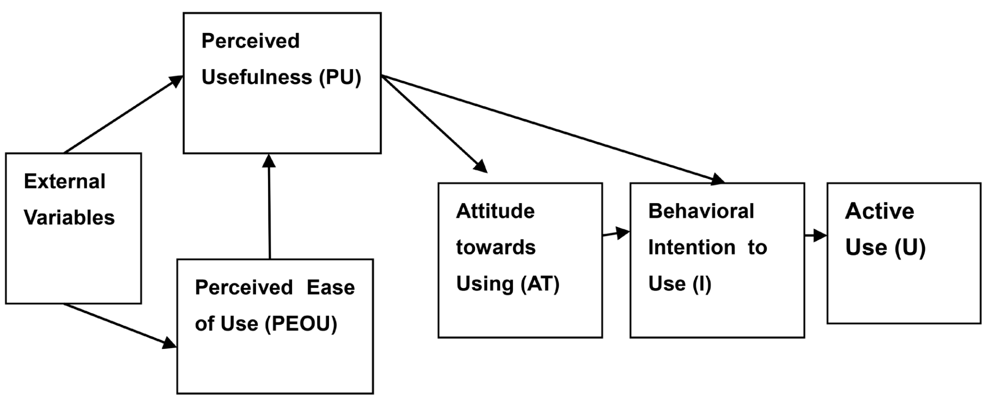

Figure 1. Technology acceptance model adapted from (Davis et al., 1989).

opinions and decisions of competitors and customers play a key role in the adoption of such technologies and can be seen in the adoption of other technologies such as e-payment and e-learning platforms (Nayanajith & Damunupola, 2018; Utami, 2017). To put it another way, it's believed that when a person thinks that people who are important to him/her (such as competitors and customers) think he/she should use a system such as crowd-logistics platforms, he or she incorporates those ideas into his or her own belief systems and so perceives the system more useful in its purpose (Venkatesh et al., 2003).

2.5.2. Perceived Enjoyment

Following subject norm, the concept of enjoyment is another important construct in the TAM model, it is based on intrinsic motivation (Deci, 1975). In the context of information system usage, it is defined as 'the extent to which an individual perceives utilizing a certain system to be delightful in its own right," without regard to the repercussions of the system's use on one's performance (Abdullah & Ward, 2016). Perceived Enjoyment is an important factor in explaining crowd-logistics platform adaptation (Chin & Ahmad, 2015; Winarno et al., 2021). Previous studies showed that perceived enjoyment significantly impacted perceived usefulness of digital based platforms such as crowd-logistics platforms and increases users' intention to use a platform especially in developing economies (Chin & Ahmad, 2015).

2.5.3. Computer Anxiety

Another construct this research considers is anxiety. It has been explained by researchers as "evoking anxious or emotional reactions when it comes to performing a behavior" (Widiyasari & Achadiyah, 2019). In the context of computer usage, computer anxiety is described as "the tendency of an individual to be uneasy, apprehensive, or fearful about the current or future use of computers in general" (Abdalmohsen & Alshammari, 2018). Many researchers who have studied the role of computer anxiety in digital technologies based platform such as crowd logistics acceptance or decreased usage, have concluded that computer anxiety is associated with avoidance or less use crowd logistics platforms or technologies (Abdalmohsen & Alshammari, 2018; John, 2013; Karsten et al., 2012; Widiyasari & Achadiyah, 2019). Computer anxiety plays an important role in crowd logistics platforms adoption in SME's (Abdalmohsen & Alshammari, 2018). This is because individuals who are anxious about using computers are more likely to be reluctant to adopt digital technologies based platforms such as crowd-logistics systems (Achim & Al Kassim, 2015; Abdalmohsen & Alshammari, 2018).

2.5.4. Experience

Additionally, experience is an important construct that must be considered in the context of the Technology acceptance model. Experience (XP) is regarded as "the best-studied moderator variable in TAM according to Olumide and Phd (2016). T For interactive digital platforms, the user experience has been defined as the perceptions that users develop of the platform (Azam et al., 2010). There have been a wide range of outcomes from encounters, including summary evaluations, emotional reactions (such as whether one feels positive affect in interaction), or behavioral changes. Researchers demonstrated that experience played a vital role in explaining digital based technology adoption (Azam et al., 2010; Hornbæk & Hertzum, 2017; Pangaribuan & Wulandar, 2019; Venkatesh et al., 2003). These experiences can either be positive or negative. In general, those who have had favorable experiences are more likely to have positive sentiments about the crowd-logistics system's usability.

2.5.5. Perceived Risks

Finally, researchers have linked Crowd-logistics platforms to concerns such as delays in delivery and theft of goods in prior studies and have cited it as a key determining factor in businesses adopting such platforms. The perceived risk associated with e-services such as crowd-logistics is a combination of uncertainty and loss expectations associated with a transaction, which discourages users from adopting the service and changing their behavior (Featherman & Pavlou, 2003). Crowd sourcing platforms and a variety of e-services have been proven to be adopted and used more frequently when perceived risk is taken into account. As a result, Lai (2017) revealed that including the element of perceived risk into the extended TAM model improves its accuracy in predicting behavioral intention to utilize crowd-sourcing platforms. Furthermore, perceived risk has been highlighted as a disincentive to the adoption of digital based technologies such as e-payment systems by users on a number of occasions (Chin et al., 2015). With regard to high-risk technology platforms in general, the perceived risk appears to reduce the motivation to employ and adopt such technologies (Kidiyoor, 2016).

According to this study, if SME's perceive that adopting crowd-sourcing platforms entails more risks than advantages, they will be less inclined to use such technology. Perceived risk is therefore defined as an unplanned scenario with possibly negative consequences that prospective SME users should be aware of prior to embracing the use of crowd logistics platforms for their operations. In **Figure 2**, we observe a much more expanded TAM model which considers perceived risk as a key component.

3. Research Methodology Adapted from (Davis et al., 1989)

3.1. Bayesian Inference Model

Based on existing literature (Schmid, 2022; Paucar et al., 2021; Liao et al., 2018) this study adopts the Bayesian inference using Markov Chain Monte Carlo (MCMC) approach to analysis the data. Monte Carlo method provides a numerical approach for solving complicated functions. According to Pooley and Marion (2018), the use of Bayesian inference for statistical models enlarges the range of usable models for formulation of more complex statistical models, it also allows non-deterministic knowledge that are difficult to describe with logic

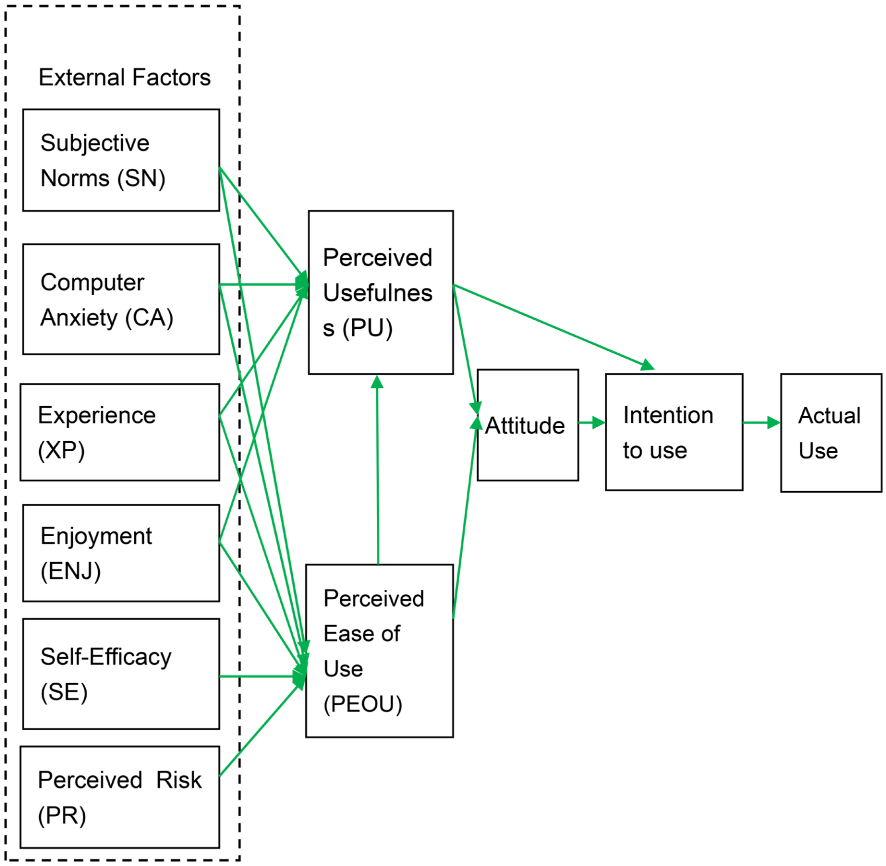

Figure 2. Research Models adapted from (Liao et al., 2018).

to be represented as a prior distribution and explicitly reflects it in evaluation of explanations (Ishihata et al., 2011). Markov Chain Monte Carlo (MCMC) is particularly useful in Bayesian interference. Thus, to generate a sample from $P(y)$, given we know $f(y)$ but not *K*. As such, we do not know $P(y)$, which can be expressed as;

$$P(y) = \frac{f(y)}{K} \tag{1}$$

MCMC allows us to estimate $P(y)$ even if we do not know the distribution by utilizing a function $f(y)$ that is proportional to the target distribution $P(y)$. We focus on stochastic models that contain parameters θ and latent variables *y*. As such the Bayes theorem is given as follows:

$$p(\theta \mid y) = \frac{p(y \mid \theta)\, p(\theta)}{p(y)} = \frac{p(y \mid \theta)\, p(\theta)}{\int p(y \mid \theta)\, p(\theta) \mathrm{d}\theta} \tag{2}$$

To clearly demonstrate how the Bayesian approach functions (Ishihata et al., 2011), in order to calculate the posterior $p(\theta \mid y)$, we need to calculate the product of the likelihood $P(Y \mid \theta)$ and the prior $p(\theta)$ over a normalizing factor (the evidence). As the integral term for the normalizing factor is often complicated and unknown; but the posterior is proportional to the product of the likelihood and prior. For numerical stability during computational simulation, we utilize the log function to transform our data samples and as such calculate the log of the unnormalized posteriror. Hence the posterior distribution is propositional to the likelihood multiplied by the prior distribution as follows:

$$\ln p(\theta \mid y) \propto \ln p(y \mid \theta)\, p(\theta) \tag{3}$$

We first initialize to some values of θ, for $t = 1, 2, 3, \cdots, N$ we propose θ based on a proposal distribution *q*. Then we calculate for the acceptance ratio *r* and acceptance probability *A* (Ishihata et al., 2011; Zhang & Mahadevan, 2003).

$$r\left(\theta^*, \theta^{(t)}\right) = \exp\left(\frac{\ln f\left(\theta^* \mid y\right)}{\ln f\left(\theta^{(t)} \mid y\right)}\right)\frac{q\left(\theta^{(t)} \mid \theta^*\right)}{q\left(\theta^* \mid \theta^{(t)}\right)} \tag{4}$$

$$= \exp\left(\ln f\left(\theta^* \mid y\right) - \ln f\left(\theta^{(t)} \mid y\right)\right)\frac{q\left(\theta^{(t)} \mid \theta^*\right)}{q\left(\theta^* \mid \theta^{(t)}\right)} \tag{5}$$

Finally, we accept the new θ according to acceptance probability *A*. Here we are defining *f* as the unnormalized posterior, where,

$$f(\theta \mid y) = p(y \mid \theta)\, p(\theta) \tag{6}$$

To know if MCMC has converged we examine the trace that is, the plot of θ over iterations. As the newly proposed θ is dependent on the current θ we expect some auto-correlation in the Markov chain as the samples are not completely independent. As such it can be shown that the error of the estimation in MCMC is,

$$\sigma^2 \approx \frac{\tau}{N} Var_{p(\theta|y)}[\theta \mid y] \tag{7}$$

where τ is the integrated auto-correlation time of the chain and represents the steps needed before it is no longer dependent. We use an effective sample size $\frac{N}{\tau}$ to account for the auto-correlation. Thus, to minimize error we reduce the auto-correlation and increased the number of samples. Our approach to reducing auto-correlation is via thinning, that is, taking the *n*th sample after convergence for constructing the distribution. For further studies on Bayesian Inference using MCMC you can refer to, (van Ravenzwaaij et al., 2018).

To ensure the reliability of the study scales of all variables are referenced from previous research. The six antecedent variables, including: perceived experience, subjective norms, enjoyment, computer anxiety and self efficacy are adapted from (Abdullah & Ward, 2016; Sorce & Issa, 2021). With respect to the antecedent perceived risked, we measured it with the scale used by (Chin et al., 2015; Lai, 2017). The 7-point Likert scale was employed; with scores ranging from strongly disagree to strongly agree. As a result, we created a questionnaire with 32 items to examine the essential factors in this investigation. **Table 2** presents the survey items and sources.

Table 2. Survey items and sources.

Construct	Item	Source
Experience (XP)	XP1: I think that using CLP would improve my business performance. XP2: I think CLP is advantageous to my business XP3: Using CLP increases my productivity XP4: Using CLP increases my efficiency in serving my customers XP5: Using CLP has increased my customer base XP6: Using CLP provides me with extra income	(Abdullah & Ward, 2016; Sorce & Issa, 2021)
Self Efficacy (SE)	SE1: Learning how to use CLP is easy for me SE2: I find CLP time sensitive and easy to use SE3: My interaction with CLP is clear and understandable SE4: It is easy for me to adapt to CLP and become skillful at its use SE5: I can easily become a CL supplier or consumer	(Abdullah & Ward, 2016; Sorce & Issa, 2021)
Subjective Norms (SN)	SN1: People who are important to (friends, family etc.) think I should use CLP SN2: People who influence my behavior (customers, competitors, etc) think I should use CLP in my business SN3: Most people surrounding me use CLP in their business SN4: In general the African community is supportive of the use of CLP in business	(Abdullah & Ward, 2016; Sorce & Issa, 2021)
Computer Anxiety (CA)	CA1: I have the resources (e.g. devices, internet or apps) necessary to use CLP CA2: I have the knowledge necessary to use CLP	(Abdullah & Ward, 2016; Sorce & Issa, 2021)
Perceived Enjoyment (PE)	CA3: Using CLP is fun and enjoyable CA4: Using CLP is entertaining CA5: Using CLP is adventurous	(Abdullah & Ward, 2016; Sorce & Issa, 2021)
Perceived Risk (PR)	PR1: On the whole considering all factors involved, using CLP would be risky to my business PR2: CLP are dangerous PR3: I think using CLP would add great uncertainty to my business	(Chin et al., 2015; Lai, 2017)
Crowd Logistics Platforms (CLP)	CLP1: I have used CLP before in my business CLP2: I intend to continue using CLP in the future (or keep using it) CLP3: I predict I will use CLP in my business in next few months CLP4: I think CLP is an important mechanism to run my business	(Abdullah & Ward, 2016; Sorce & Issa, 2021)

3.3. Data Collection

This study employed the purposive sampling approach where participants were chosen based on their characteristics and aims of the investigation. As such, our research selected SME owners across Africa who had at least received a high school diploma. These SME owners were supposed to have been in operations for at least a year. An online poll was sent across Africa through their social media groups on *Facebook*, *WhatsApp* and *Telegram*. A population size of 1000 group members was supplied with a URL link to the survey to answer the questionnaire individually at their convenience. Follow up reminders were issued frequently over a one-month period. To guarantee privacy all the questions were gathered anonymously. For each portion of the questionnaire; the researcher offered specific instructions to assist participants answer individual questions truthfully. Table 3 presents a descriptive statistics of the respondents of this research.

A filter question was used to identify persons who owned SME's and had some awareness of crowd-logistics platforms. These individuals are more likely to be current on logistics and delivery trends while also having some understanding of how these platforms work. Finally, while 135 replies were received, only 130 were complete and could be analyzed. This data set is sufficient to run a Bayesian inference model on (Paucar et al., 2021).

Monte-Carlo is a mathematical term that refers to the method of estimating posterior parameters using random sampling in order to analyze the acquired parameters. The MCMC sampling technique is carried out by combining the well-established and dependable Metropolis-Hastings algorithm with the No-U-Turn Sampler (NUST) on the data. The NUST is especially advantageous for sampling from models with a large number of continuous parameters. And the Metropolis-Hastings

Table 3. Descriptive statistics of the sample (researcher's own construct).

Variable	Label	Frequency	Percent (%)	Cumulative Percent (%)
Gender	Male	70	53.4%	53.4%
	Female	60	45.8%	100%
Age (year)	15 - 25	13	9.9%	9.9%
	25 - 35	64	48.9%	58.8%
	35 - 45	48	36.6%	95.4%
	45 and above	6	4.6%	100%
Employment Status	Student	37	28.7%	28.7%
	Self- Employed	12	9.3%	38%
	Entrepreneur and Student	12	9.3%	47.3%
	Entrepreneur and Employed	66	52.7%	100%
	Retired	0	0%	0%
Level of Education	High school graduate	5	3.8%	3.8%
	Diploma/Vocational/Technical Institute	5	3.8%	7.6%
	Graduate with Bachelor Degree	65	49.7%	57.3%
	Graduate with Masters Degree	56	42.7%	100%
SME owner (year)	Less than 5 years	92	70.2%	70.2%
	5 - 10 years	31	23.7%	93.9%
	11 - 20 years	4	3.1%	97%
	20 years and above	5	3.0%	100%

algorithm samples randomly from a posterior distribution in order to estimate the properties of its parameters across a large number of repetitions using a specific algorithm to successively generate a Markov Chain for a number of underlying components. PyMC3 is a Python library for Bayesian statistical modeling and Probabilistic Machine Learning, with a particular emphasis on advanced Markov chain Monte Carlo (MCMC) and variational inference (Salvatier et al., 2016).

3.4. Reliability and Validity

The Bayesian Cronbach's alpha is used to determine the reliability and validity of the method. It was calculated using the Python pingouin module. **Table 4** contains the data. We present a normality test focused on the endogenous variables of our research respondents in **Figure 3** below.

As a pre-requisite for the validity of the model, reliability analysis in **Table 4** has been conducted. The Cronbach's Alpha values were calculated for each construct. The TMA model indicated a satisfactory fit. Cronbach's alpha values range from 0.8728 to 0.9849 indicating high overall internal consistency among the items under each of the constructs, which is greater than the acceptable criterion of 0.70 (Thorndike, 2016) confirming the measurement model's dependability.

3.5. The Bayesian Repeated-Measures ANOVA

Prior to evaluating the fitness of the conceptual model described in **Table 4**, it is

Table 4. Bayesian single-test reliability results (Researcher's Own Calculations)

Construct	Cronbach's Alpha	Posterior mean (95% CI)
Experience (XP)	0.9849	[0.981, 0.989]
Self-Efficacy (SE)	0.9728	[0.965, 0.979]
Subjective Norms (SN)	0.9733	[0.965, 0.979]
Computer Anxiety (CA)	0.9242	[0.894, 0.946]
Perceived Enjoyment (PE)	0.9670	[0.883, 0.935]
Perceived Risk (PR)	0.9120	[0.883, 0.935]
Crowd Logistics Platform (CLP)	0.8728	[0.834, 0.904]

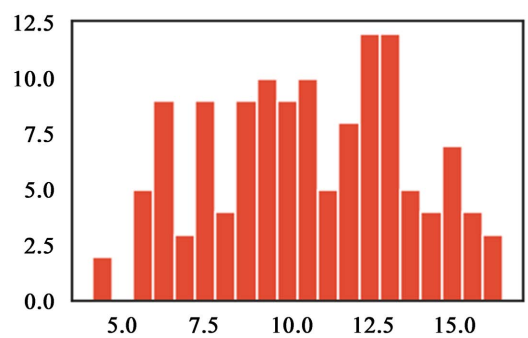

Figure 3. Normality test of endogenous variables using a histogram of the data (Researcher's Own Construct).

important to compare the scale value of the technology acceptance model that the participating SME owners showed regarding the adoption of crowd logistics platforms and its corresponding technology. The data was analyzed using a Bayesian repeated-measure ANOVA (Schmid & Stanton, 2019). In terms of their prior odds, all hypotheses are considered to be equally likely. Thus, the default Microsoft Excel prior for fixed effects with alpha (α) = 0.5. was used in the study. Results from the Bayesian ANOVA are summarized in **Table 5**. Hypotheses were tested against the null model in order to see how well they predicted outcomes. The seven latent variables served as categorical predictors. All possible models were considered, but we ruled out any that had substantial evidence for their existence (H_0). Because they're considered implausible, we also excluded models with interactions but no main effects. As can be seen in **Table 6**, the models that have been left over provide at least some support for the hypothesis that the combined effects are real. **Table 5** provides a summary of our results.

A one-way repeated ANOVA was conducted to examine the adoption of crowd logistics platforms for SME's in Africa. The F test statistic is 95.57407 and the corresponding p-value is 0.0000199. Since the p-value is less than 0.005, we reject the null hypothesis and conclude that there is a statistically significant mean between our constructs. These results show substantial evidence for the acceptance of these logistical platforms by SME owners to be high and confirms the robustness of these results against changes in the priors.

Table 5. Model comparison of the Bayesian ANOVA (Researcher's own construct)

Construct	Count	Sum	Average	Variance	%Error
Experience (XP)	130	304	2.338	3.559	8.143
Self-Efficacy (SE)	130	499	3.838	1.222	0.562
Subjective Norms (SN)	130	478	3.676	0.841	1.388
Computer Anxiety (CA)	130	476	3.662	0.815	2.765
Perceived Enjoyment (PE)	130	471	3.654	0.717	4.234
Perceived Risk (PR)	130	475	2.908	0.833	2.759
Crowd Logistics Platform (CLP)	130	378	3.754	1.092	6.882

Table 6. Bayesian ANOVA Test result summary (Researcher's own construct)

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Rows	692.7269231	23	30.11856	155.2256	5.07E−05	1.53289
Columns	2392.217949	129	18.54433	95.57407	1.99E−05	1.219229
Error	575.6897436	2967	0.194031			
Total	3660.634615	3119				

3.6. Posterior Analysis

To derive posterior estimates for the model's unknown variables, we investigate locating the Maximum Posteriori (MAP) point and producing summary statistics using MCMC sampling methods, which is presented in **Table 7** below.

The maximum a posteriori (MAP) estimates for a model are the mode of the posterior distribution and are often determined using numerical optimization techniques. While this is frequently a quick and simple procedure, it simply provides a point estimate for the parameters and might be misleading if the mode does not represent the distribution. PyMC3's *find MAP* function implements this feature (Salvatier et al., 2016). **Figure 4** presents the posterior samples of degrees of freedom (mu) and scale (sigma) parameters of TAM model. Each plotted line represents a single independent chain in parallel.

3.7. Model Specification

Because the syntax is comparable to statistical notation, specifying this model in PyMC3 is simple. Each line of Python code, for the most part, corresponds to a line in the model notation. We import the necessary components from PyMC3 and run the model. This is the model statement that describes the priors and likelihood. In this case, mu is defined as a stochastic variable (we want a chain of sampled values for it), and we offer a prior distribution and hyper-parameters for it. The Normal likelihood function is used, with one parameter to be estimated (mu) and one known (denoted as sigma). Our "dependent variable" is defined as observed=data, where data is collected from respondents. The research has an acceptance rate of 0.872115 and the auto-correlate of degrees of freedom (mu) and scale (sigma) parameters of the model is displayed in **Figure 5**.

3.8. Model Fitting

The data run through the PyMC3 model and the results indicate a good fit to the

Table 7. Text-based output of common posterior statistics (Researcher's Own Calculations).

Parameter	Mu [0]	Sigma [0]
Mean	10.586	2.789
SD	1.411	1.442
Hdi_3%	7.879	0.983
Hdi_97%	13.287	5.558
Mcse_mean	0.006	0.008
Mcse_sd	0.004	0.006
Ess_bulk	0.004	0.006
Ess_tail	42,537.0	42,752.0
R_hat	1.0	1.0

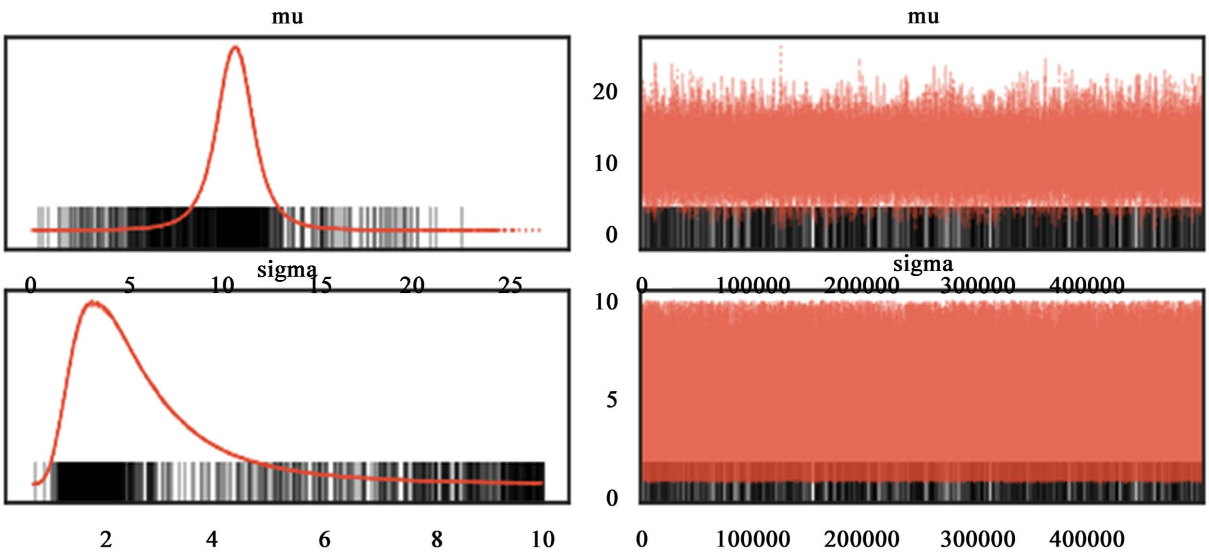

Figure 4. Posterior samples of degrees of freedom (mu) and scale (sigma) parameters of TAM model. Each plotted line represents a single independent chain in parallel. The x-axis represents frequency and sample values (Researcher's Own Calculations).

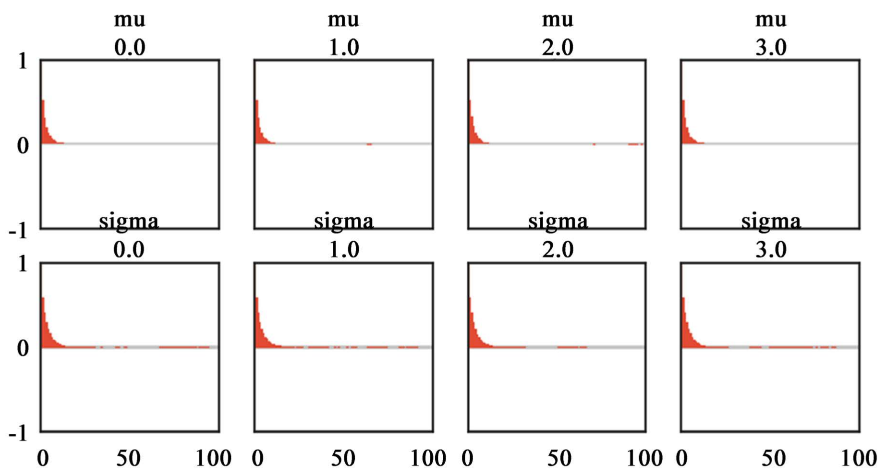

Figure 5. Auto-correlate of degrees of freedom (mu) and scale (sigma) parameters of the Crowd-Logistics TAM model (Researcher's Own Calculations).

model. We plot the distribution of the model by plotting many of our sampled volatility paths on the same graph. Each is rendered partially transparent as such the regions where many paths overlap are shaded more darkly.

As can be seen the model correctly infers the relationship between perceived risk, perceived experience, subjective norms, enjoyment, computer anxiety and self efficacy and the perceived usefulness of the model. In addition, the results indicate that perceived risk is a strong factor that affects SME owner's willingness to adopt crowd logistics platforms. In other words, SME owner's are more likely to use crowd logistics platforms if they feel the inherent perceived risk can be mitigated and they will benefit from using the platform. The normality test of our data (**Figure 3**) showed that our data is normally distribution and all hypothesized relations were strong.

4. Discussions and Findings

The primary goal of this study was to infer the relationship between perceived risk, perceived experience, subjective norms, enjoyment, computer anxiety, and self efficacy, as well as the perceived usefulness of the model, utilizing the Bayesian model using the PyMC3 model in Python. We examined the above linkages using the TAM model; the results show that the determinants of intention to use crowd logistics platforms based on perceived utility and perceived use of the platform have substantial effects. Many respondents felt it had a big impact on their business processes; they felt it gave their company an advantage over competitors if they were able to use crowd-logistics platforms.

We measured the effect of self efficacy on crowd logistics platforms because many of the respondents had been in business for less than 5 years, and the results show that SME owners in Africa are more likely to adopt crowd logistics platforms if the processes are simple, easy to understand, and time sensitive. SME owners placed a high value on the decisions of competitors and consumers, and as a result, subject Norms had a substantial impact on the perceived utility of crowd logistics platforms and their adoption. It emphasizes the competitive advantage that SME owners who use crowd logistics platforms want to establish for their companies.

The perceived enjoyment of crowd logistics platforms also suggested that SME owners recognized a correlation between utilizing crowd logistics platforms and the intention to use these platforms, implying that if SME owners enjoy crowd logistics platforms, they will have a good experience. Having the right resources and tools is vital for SME owners who want to use crowd logistics platforms, but it has no bearing on their decision. This implies that SME require resources to facilitate their use of these platforms, therefore assistance with, or provision of, these resources and tools will have an impact on use. SME owners' usage of these platforms was significantly correlated with their perception of risk. Fear of theft and loss was a major obstacle to the adoption of these platforms by many SME owners. This emphasizes the significance of establishing security and trust for both the audience and SME owners by implementing safe technology such as block chain encryptions (Rejeb et al., 2019). Finally, because many SME owners in Africa use computer platforms on a regular basis, computer anxiety had little impact on their decisions to adopt crowd logistics platforms, as highlighted by (Sriningsih et al., 2020).

Moreover, re-examining the TAM model using the Bayesian inference model yielded superior findings in terms of the number of statistically significant parameters, which is consistent with previous research.

The model produced findings from **Table 5** that indicated a good fit (Asuero et al., 2006), such as a R Hat or potential scale reduction (PRSF) value of 1.0, which is considered good (Gelman & Rubin, 1992). The Bayesian model with SEM is a robust approach since it does not require any distribution function assumptions such as normality. As a result, this study demonstrates that a Bayesian approach can offer superior results for assessing TAM and forecasting user behavior. The raw individual random observations are emphasized in the formulation and development of the Bayesian approach rather than the sample covariance matrix.

Furthermore, Bayesian statistics is becoming more popular in mainstream psychology, as well as management and information systems. It offers academics a variety of theoretical and practical advantages over the "conventional" ML technique. As the Bayesian paradigm is more integrated into information systems, researchers will have access to methodologies that are especially suited to creating cumulative knowledge.

5. Conclusion and Future Research

A wide range of practical applications could be derived from this study's findings. The study is focused on the adoption of crowd logistics platforms in the African small and medium-sized enterprises market. The findings will be helpful in the successful development and implementation of logistical platforms for large crowds and businesses. According to this study, perceived risk is one of the factors that deter businesses from adopting crowd logistics platforms. Smart contracts and other appropriate technological models, can help developers better understand how users perceive the risk of using these platforms and how to mitigate that risk.

The growing popularity of the Internet and Internet-based logistics applications presents SMEs with untapped growth potential, according to this study. Logistics platform developers can take advantage of a growing demand from African businesses to create new platforms that cater to the unique business landscape in the African continent.

An increasing number of African SME businesses are embracing the use of information systems, and this study contributes to this body of knowledge by conducting a survey of African SME businesses.

6. Limitations of the Study

Although this study gives some insight into Small and Medium Scale Enterprises' intentions to use crowd logistics platforms in the context of Africa, numerous limitations must be addressed in future research. The study was carried out on chosen corporate social media accounts in Africa. It did not use a holistic strategy in the selection procedure to examine SME owners from a bigger sample across Africa, which may limit the findings' generalizability. Future studies should use a more random sample of African countries.

Also, given that research on Crowd logistics is still in its early stages, the proposed model in this study requires greater sophistication. For example, while this study found a link between perceived risk on SME owners and crowd logistics platform adoption intention, we measured perceived risk using a synthetic manner. A variety of literature provides various aspects of risk associated with technology uptake. As a result, it is possible to conceptualize several factors of perceived risk associated to SME's for crowd logistics adoption. Future research could improve the model by evaluating other components of perceived risk and including conditional factors.

PyMC3 in Python is used for analysis in this study. It is possible to suggest that there is a wide range of libraries in emcee in Matlab, bayesianmh in STATA and STAN, JAGS and Open BUGS in R that may be used to provide greater variety and wider analysis.

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Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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