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The Adoption of Whistleblowing Mobile Applications in Whistleblowing Services: Deep Learning Based SEM-Neural Network Approach

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Abstract
Whistleblowing Mobile Applications are becoming a popular delivery method for whistleblowing services, allowing employees, suppliers, and collaborators to send reports of wrongdoing and alleged. This study examines the factors influencing the employee's behavioral intention to use whistleblowing mobile applications in Ethiopian public and private organizations.This study included four new elements to the Unified Theory of Acceptance and Use of Technology (UTAUT) model: trust, perceived privacy risk, perceived security risk, and information quality. Data was gathered from 689 users of the smartphone application from Ethiopia. This study performs dual-stageanalysis by applying deep learning-based Partial Least Square-Structural Equation Modelling (PLS-SEM) & Artificial Neural Network (ANN) methods. Structural equation modeling (SEM) was used to identify essential characteristics influencing consumers' approval of government mobile whistleblowing services. A neural network model was employed in the second stage to confirm SEM results and evaluate the relative relevance of determinants of government mobile whistleblowing services acceptability. The deep learning-based two-step PLS-SEM & ANN results revealed that perceived privacy risk, performance expectancy and trust are the most important factors influencing user intention to use mobile whistleblowing application. The findings of this study have contributed theoretically to previous research on whistleblowing services and have practical implications for decision-makers involved in the development and deployment of mobile whistleblowing services in Ethiopia.
Keywords: whistleblowing mobile application, whistleblowing, UTAUT, Perceived Privacy Risk Perceived Security Risk, Trust, Information quality

Introduction
The Organization for Economic Co-operation and Development (OECD) defines Digital Government as "the use of digital technologies, as an integrated part of governments' modernization strategies, to create public value" (OECD, 2014). Governments all over the world are now aware of the power of ICTs and digital government in advancing and transforming public institutions, as well as the public-sector environment in general, and their service delivery capacities (Carvalho & Marques, 2019; Kim, 2020). Governments also re-engineering their whistleblowing services to include mobile applications to provide online whistleblowing services (Veeramootoo, Nunkoo, & Dwivedi, 2018). Whistleblowing can act as a crucial check on human rights abuses, corporate malfeasance, and corruption (Kang, 2023).

Many governments are attempting to develop whistleblowing mobile applications to provide a secure channel that allows employees, suppliers, and collaborators to send reports of wrongdoing and alleged offenses to the organization or administration (Biletskyi, 2022; Costa, 2023). Citizens, on the other hand, are wary and skeptical when it comes to using whistleblowing Mobile Applications (Dwivedi et al., 2017). Due to the portability of mobile devices and their ability to provide 24/7 access to useful services via the Internet, mobile applications are increasingly widely used in all corporate and governmental sectors (Zhu & Hou, 2021; Al-Masaeed & Love, 2015).

Digital technologies have been advancing rapidly. Technologies ranging from automation to IoT have been game-changers in public service delivery (Criado & Gil-Garcia, 2019). AI and deep machine learning (ML) have enabled machines to surpass humans in many types of information processing, e.g., visual and pattern recognition, in which robots excel over humans (Zohuri & Rahmani, 2020; Janiesch, Zschech & Heinrich, 2021). The adoption of digital technology for public service delivery can shift the model, from being reactive to citizens' needs to becoming proactive in knowing what their needs will be in the future. It can provide a better platform for the participation of all stakeholders, and especially, allow for reflecting citizen preferences in the policymaking process for public services (Walker, 2020). But digital technologies have changed the practice of whistleblowing, with a growth in new tactics and strategies based on encryption-based communication tools (Di Salvo, 2021; Olesen, 2022; Walle, 2020, Mulualem Walle, 2020).

Mobile phones may thus be the most viable electronic conduit for encouraging the widespread adoption of online public services. Advanced mobile devices, such as smartphones with whistleblowing apps, give enormous opportunities for government organizations to improve the protection of whistleblowers' identities and accessibility, as well as encourage citizens to participate in anti-corruption measures (Olesen, 2022; Walle, Janowski & Estevez, 2018). Whistleblowing Mobile apps are a type of digital assistance and are one of the methods via which people can blow the whistle without being constrained by time or location. Many government agencies in Ethiopia have begun to engage in and commit funds to programs that will allow them to mobilize their whistleblowing services via mobile applications. Mobile applications that provide online whistleblowing services are seen as new ways to anonymously and confidentially report wrongdoings, as well as to connect and interact with Ethiopian government stakeholders. However, the adoption of mobile digital government services has not yet met its goals, according to surveys, and similar electronic government programs have either failed or experienced a sluggish adoption process (Gao, Krogstie & Siau, 2014). Some internal and external whistleblowers continue to prefer traditional whistleblowing communication channels to report wrongdoing activities (Mrowiec, 2022). As a result, it's critical to comprehend the major factors that influence their willingness to adopt whistleblowing mobile apps.

The prior studies (Talukder et al., 2020; Zabukovsek et al., 2019) applies logistics regression and only structural equational modelling (SEM). This only able to detect linear association among variables. However, this result is not acceptable to predict the complexities affecting multifaceted decision-making processes. As a result, previous studies have used machine learning approaches like artificial neural networks (ANN) as second stage of investigations entailing a single hidden layer to eradicate such constraints. Because of this, earlier studies (Sharma et al., 2018; Talukder et al., 2020; Zabukovsek et al., 2019) have used machine learning methods like artificial neural networks (ANN) as the second stage of research including a single hidden layer to eliminate such constraints. Furthermore, it is thought that the application of SEM & ANN in the area of technology adoption is quite beneficial (Zabukovsek et al., 2019). According to Huang and Stokes (2016), second stage ANN analysis with a single hidden layer is a subpar kind of ANN. Nevertheless, it is important to point out that all of the research described above used shallow SEM & ANN approaches; as a result, it was advised to employ a two stage PLS-SEM & ANN strategy based on deep neural network architecture for the best outcome (result). Due to its deep learning capability, the use of deep neural network design with two or more hidden layers would improve the accuracy of non-linear associations in the model.

Therefore, in a developing nation like Ethiopia, addressing the need for more empirical inquiries and enhancing the literature on whistleblowing mobile application technology adoption; this research aims to identify the variables that can predict a user's initiations to adopt whistleblowing mobile application. This study used the Unified Theory of Acceptance and Use of Technology (UTAUT) to better understand and forecast how whistleblowing mobile apps are used in Ethiopia. To further analyze the acceptance of whistleblowing mobile apps, it also incorporates five additional constructs: Personal Integrity, personal innovativeness, perceived privacy risk, perceived security risk, and trust. Finally, a structural equation model (SEM) was used to test the impact of determinants on whistleblowing mobile app acceptance, while artificial intelligence neural network models were used to validate SEM results and predict the importance of key determinants of whistleblowing mobile app acceptance.

2. Literature Review

2.1. Overview of Digital Whistleblowing Services in Ethiopia

Organizations all over the world implement the whistleblowing system as a mechanism to avoid and reduce the possibility of violations (Triantoro, Utami & Joseph, 2020; Stubben & Welch, 2020). An effective Whistleblowing System encourage community participation and employees of an organization to be more willing to act to prevent fraud and corruption by reporting it to those who can handle it (Maulida & Bayunitri, 2021). The digital whistleblowing system is an online platform developed specifically for corporate whistleblowing (Di Salvo & Leaks, 2020). The main aim of the digital whistleblowing system is to provide an easy and efficient whistleblowing service that guarantees the anonymity and/or confidentiality of the whistleblower during the submission of the (anonymous) report as well as in the entire further communication process. Additionally, dashboards are made available to responsible employees through digital whistleblowing systems, allowing them to manage cases effectively.

Ethiopia's comprehensive digital transformation strategy, Digital Ethiopia 2025, introduced in 2020 has significant plans to bring the country fully into the modern age by considering the nation's development plan for the years 2021–2030 (MinT, 2021). Digital Ethiopia is an initiative led by the Government of Ethiopia, to leverage digital opportunities and propel Ethiopia into an innovative, knowledge-based economy. The five priorities listed in the strategy are the establishment of a digital ID, electronic payments, e-governance, electronic commerce, and cybersecurity. The largest telecom provider in Ethiopia, Ethio Telecom, reported an exceptional increase in internet users. Ethiopia has 31.3 million data and internet subscribers with Ethio Telecom during the 2022–23 fiscal year (Ethiotelecom, 2023). This shows that organizations in Ethiopia are ready to implement digitally enabled services including digital whistleblowing systems. However, Ethiopians are still hesitant to utilize cutting-edge technologies. As a result, neither residents nor employees of organizations are able to use the resources that organizations and the government can offer in the battle against corruption and illegal actions.

Mobile applications offer workers greater flexibility, enhance workflows, improve communications, and help to make users more efficient and productive (Shieh et. al., 2014). In addition, it also helps to create a direct interaction channel between users and the organization where one can easily explore and engage as they wish (Weichbroth, 2020). Furthermore, it promotes the development of new mobile services and encourages employees and residents to engage with organizations constantly. Mobile subscriptions in Ethiopia have increased substantially in the last few years.

The Ethiopian government created the E-Services Portal to offer 341 online electronic public services from 24 service providers to individuals, non-citizens, enterprises, and governmental & non-governmental organizations (Eservice, 2023). Considering this, the government of Ethiopia is undergoing a major expansion of its network infrastructure. Recently, a variety of mobile services have been launched by government organizations as well as private organizations. One notable example is FDRE anti-corruption commission whistleblowing mobile app is Ethiopian Public Feedback System (epfs.gov.et) which provides a safe channel that allows staff members, vendors, and partners to report alleged misconduct and offenses within their organizations. The Application, which is a supplement to the web portal, is intended to guarantee total accessibility to the reporting environment and to provide a user-friendly mechanism to lead the whistleblower through the reporting procedure. The application allows the whistleblower to report written and voice reports anonymously. The application provides the whistleblower the possibility to activate custom push notifications. The app is available in 2 languages (English and Amharic) and can be localized according to requests. Employees utilized mobile services to report any unlawful activities within their organizations.

2.2 Hypothesis Development and Conceptual framework

The Unified Theory of Acceptance and Use of Technology (UTAUT) is the most common and widely used theoretical model for the acceptance of new technology. In 2003, Venkatesh et al. developed the Unified Theory of Acceptance and Usage of Technology model, which incorporates social factors and human behaviors while addressing the shortcomings of the technology acceptance (TAM) model (Venkatesh et al., 2003). It aims to explain user intentions to use an information system and subsequent usage behavior. Additionally, many studies asserted that UTAUT could be used as an effective model to comprehend the acceptance and successful application of technologies in developing countries (Abbad, 2021; Kayali & Alaaraj, 2020). Considering the unified nature of this model, UTAUT model has been chosen as the foundation for this study. UTAUT examines the acceptance of technology through four key constructs, namely performance expectancy, effort expectancy, social influence, and facilitating conditions. These constructs, however, fall short of adequately capturing all facets of whistleblowing mobile applications in government services. Five additional constructs: Personal Integrity, personal innovativeness, perceived privacy risk, perceived security risk, and trust are very important to deliver whistleblowing services to the user. Delivering any mobile services requires the concept of trust (Alkhowaiter, 2022; Arfi et al., 2021). To increase the need for trust in whistleblowing services, government agencies exchange helpful whistleblowing information with private, public, and user agencies (Walle, 2020). Providing Secured whistleblowing service is considered the primary requirement expected by whistleblowers (Sørensen, Gaup & Magnussen, 2020). Assuring the utmost confidentiality of information reported and the anonymity of users who desire it is essential to running a successful hotline. Regardless of the content of their message, everyone contacting the hotline must be guaranteed that they will not be subject to company sanctions and will be safeguarded from potential reprisal by wrongdoers if they come forward.

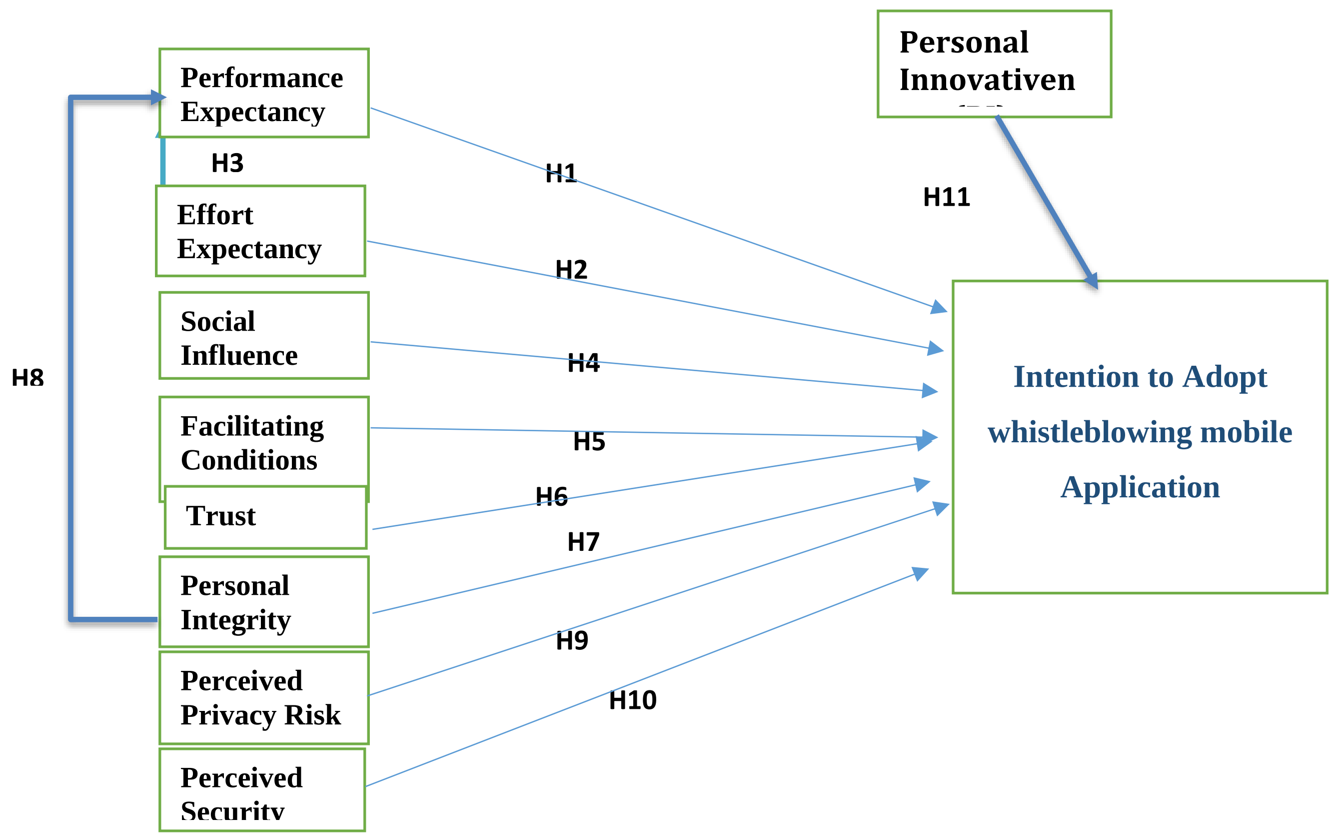

Figure 1. Proposed Research Framework (Adapted from Venkatesh et al., 2003)

2.2.1 Performance Expectancy (PE)

Performance Expectancy is conceptualized as the extent to which a person thinks utilizing the technology would help them improve their work performance (Venkatesh et al., 2003). The UTAUT model has been used in numerous studies (Venkatesh, 2022; Al-Saedi et al., 2019; Arfi et al., 2021), proving that performance expectancy is a key indicator of behavioral intention to embrace new technology. In this research, we considered performance expectancy would have a direct impact on users' behavioral intention to whistleblowing mobile applications. In this regard, Ethiopian private and public civil servants are expected to use the secured whistleblowing mobile application if they feel that using mobile applications will enable them to access government whistleblowing mobile-based services 24/7. Several studies verified that performance expectancy affects people's decisions to use mobile applications. In light of this, we suggest the following hypothesis:

H1. Performance expectancy has a positive influence on behavioral intention to use whistleblowing mobile applications.

2.2.2. Effort Expectancy (EE)

Effort expectancy is the degree of comfort and usefulness that users experience when utilizing a particular information system (Venkatesh et al., 2003). The UTAUT model supports the idea that the time and effort invested in learning a new information system affects intentions to use it. Previous research (e.g. Alkhowaiter, 2022; Venkatesh, 2022; Al-Saedi et al., 2019; Arfi et al., 2021) on technology adoption has found that behavioral intentions toward new technology are significantly influenced by effort expectancy. Other research using different acceptance models indicates that users are willing to adopt a technology if it is simple to use and doesn't take any extra work and effort. In this study, we believe that effort expectancy could have a major impact on users' behavioral intentions in using whistleblowing mobile applications. As a result, in this research, we suggest the following hypothesis:

H2. Effort expectancy has a positive influence on behavioral intention to use whistleblowing mobile applications.

H3: Effort expectancy has a positive and significant influence on the performance expectancy of using whistleblowing mobile applications.

2.2.3. Social Influence (SI)

Social influence is the perception that someone should use the new technology because other people think they should use the new system. Different studies (e.g. Joa & Magsamen-Conrad, 2022; Zhou et al., 2019; Ahmad & Khalid, 2017) argued that the reference groups influence the decision of users to adopt a new service when they have no or little knowledge of the service. Some other studies (Venkatesh et al., 2012) signal that social influences just partially influence behavioral intention and in part, they directly influence user behavior. Based on prior research, social influence is selected in this study as one of the possible predictors influencing behavioral intention. In this research, social influence is anticipated to have an impact on the decision to use whistleblowing mobile applications. As a result, in this research, we suggest the following hypothesis:

H4. Social influence has a positive influence on behavioral intention to use whistleblowing mobile applications.

2.2.4 Facilitating Conditions (FC)

Facilitating Conditions are the degree to which a person perceives that organizational and technical infrastructures required to use the intended system are available (Venkatesh et al., 2003). In this study, users believe that it guarantees the whistleblowers' identities, acceptable timelines for case receipt and settlement, the selection of impartial individuals to receive and monitor complaints, and whether both oral and written reports are acceptable are the main concerns. Users typically require help when utilizing a new technology. Additionally, other researchers have found that users avoid using new technology when the facilitating conditions are insufficient (Zhou et al., 2019; Khechine, Raymond & Augier, 2020). Considering the aforementioned reasons, it can be assumed that having excellent facilitating conditions would affect a person's choice to accept whistleblowing mobile applications. Therefore, based on the following arguments, this study articulates the following hypotheses:

H5. Facilitating conditions have a positive influence on behavioral intention to use whistleblowing mobile applications.

2.2.5 Perceived Trust (PT)

Prior Studies (e.g. Sarkar, Chauhan & Khare, 2020; Sharma et al., 2020) on technology adoption have revealed that people's perceived degree of trust in the technology may cause them to oppose or be reluctant to use it. To find out the users' attitudes toward the use of new systems, trust as a factor plays a major influence on users' intention to use the new system. Many researchers (e.g. Alkhowaiter, 2022; Arfi et al., 2021) asserted that trust was a key determinant factor that affected the adoption of new technologies. Even Though there are many factors, lack of confidentiality and transparency of the whistleblowing procedures causes distrust and leads to whistleblowers being reluctant to use the whistleblowing mobile applications. As a result, it's critical to make sure that users are confident in these services before they conduct transactions through mobile applications (Montazemi & Saremi, 2013). In this research, we aimed to know the users' interest in taking the risk of trusting whistleblowing mobile applications. Therefore, respondents' behavioral intentions towards whistleblowing mobile applications will be positively influenced if they believe the technology to be trustworthy. Therefore, based on the following arguments, this study articulates the following hypotheses:

H6. Trust has a positive influence on an individual's behavioral intention to use whistleblowing mobile applications.

2.2.6. Personal Integrity (PI)

Personal integrity is conceptualize as the habit of being sincere and genuine with oneself and others, as well as the deliberate alignment with one's own personal behaviors and acts with one's own morals and ethics (Hartman, DesJardins & MacDonald, 2011). Personal integrity emerged as a dynamic intrinsic quality of individuals. Numerous studies (walle, 2020; Biletskyi, 2022) show that whistleblowers are frequently driven by their own sense of morality and a sincere desire to safeguard the public. The majority of people voice concerns about illegal and dangerous workplace behaviors because they are unwilling to engage in behavior they regard to be immoral, even though doing so may have a detrimental effect on their employment. Considering the above arguments, it is hypothesized that the decision to use and accept whistleblowing mobile applications is influenced by the personal integrity. Therefore, based on the following arguments, this study articulates the following hypotheses:

H7: Personal Integrity has a positive influence on an individual's behavioral intention to use whistleblowing mobile applications.

H8: Personal Integrity has a positive and significant effect on performance expectancy of using whistleblowing mobile applications.

2.2.7. Perceived Privacy Risk (PPR)

According to Papadomichelaki and Mentzas (2012), privacy is defined as the ‘protection of personal information, not sharing personal information with others, protecting anonymity, secure archiving of personal data, and providing informed consent’. Privacy issues have frequently been brought up in the world of online environment. According to prior research (e.g. Chopdar, 2022; Hérault and Belvaux, 2014), users' privacy concerns are a significant barrier to the adoption of technology-related products and services, and privacy issues lessen the perceived ease of technology. Whistleblowers are very sensitive about their personal data. It is believed that Compliance officers will be required to follow very specific procedures when handling personal data, particularly as it pertains to issues of whistleblowing reports. Further, the potential misuse of personal information may worsen individuals’ privacy concerns about various whistleblowing technologies. Thus, when a user perceives a greater privacy risk/loss compared to the benefits, they are less likely to adopt a whistleblowing mobile application. In this study, Perceived Privacy risk (PPR) is conceptualized as the user's perception regarding risk associated with their personal information, unauthorized use, and sharing to third parties without their consent while using whistleblowing mobile applications. A greater PPR level is thought to lessen their desire to use whistleblower mobile applications. As a result, in this research, we suggest the following hypothesis:

H9. Perceived Privacy Risk (PPR) negatively affects the behavioral intention (BI) to use whistleblowing mobile applications.

2.2.8. Perceived Security Risk (PSR)

The concept of perceived security risk was equated with users' perception modes of storage and transfer of information in an online context. Flavi´an C & Guinalíu M. (2006) defines perceived security risk as "protecting the integrity, confidentiality, authentication, and non-recognition of relationships". According to a study on the whistleblowing system, whistleblowers were less likely to use mobile devices when there was a significant degree of security risk (Jurgilewicz et al., 2020). In this study Perceived security risk (PSR) conceptualized as users' perception about the lack of protection of information and chances of hacking and security breaches associated with whistleblowing mobile applications usage. It is believed that higher degree of Perceived security risk decreases the users desire to use whistleblower mobile applications. As a result, to understand the impact of perceived security risk on adoption of whistleblowing mobile application, the next hypothesis is suggest:

H10. Perceived Security Risk (PSR) negatively affects the behavioral intention (BI) to use whistleblowing mobile applications.

2.2.9 Personal Innovativeness (PInn)

Personal innovativeness can be conceptualized as the extent to which a person thinks that he or she has a favorable disposition toward using novel, innovative technologies (Agarwal and Prasad, 1998). Personal innovativeness reflects a person's inherent innovative personality related characteristic. According to Shaw and Sergueeva (2019) people who are more innovative personalities tend to be more likely to want to use new technologies. They also stated that higher risk-tolerance individuals are more inclined to try out new technologies because they have more favorable attitudes toward using technology. Prior research (Farooq, 2017) has found a significant link between personal innovativeness and behavioural intention. In this research, we assert that personal inventiveness will serve as a constructive moderator of the effect of performance expectancy on perceived value. This essentially indicates that users who are innovative will strive to incorporate the use of cutting-edge whistleblowing mobile applications into their daily life to blow the whistle for any unlawful activities observed. As a result, this study formulates the following hypotheses.

H11: Personal innovativeness has a positive effect on intention to adopt whistleblowing mobile applications.

In line with the above discussion, Figure 1 shows the suggested research model for these study. It is suggested that UTAUT constructs, along with Personal Integrity, personal innovativeness, perceived privacy risk, perceived security risk, and trust as five additional constructs, are what drive the acceptance of whistleblowing mobile applications.

3. Research methodology

3.1. Measurement Development

The general methodology used for this study is depicted in Figure 2. The proposed UTAUT-based model was tested through a two-step process. The first step was Structural Equation Modeling (SEM) which is a powerful multivariate analysis technique that is widely used in the social sciences. The second step was the Artificial Neural Network (ANN) for its ability in nonlinear modeling. In this study, a close-ended questionnaire was developed to collect data for answering the research questions and test hypotheses. Prior to collecting data on a large scale, a pilot study was carried out in the month of November 2022 to evaluate the validity of the questionnaire. The first part of the questionnaire contains questions regarding background information and the second part contains questions developed based on the nine constructs of the proposed UTAUT model as depicted in figure 1. This instrument was validated by previous studies. To meet the needs of this study, the questionnaire instruments were adapted and the wording changed as required without altering the original scale. Additionally, the items were written in simple and clear language to motivate respondents to express their opinions without any restraint.

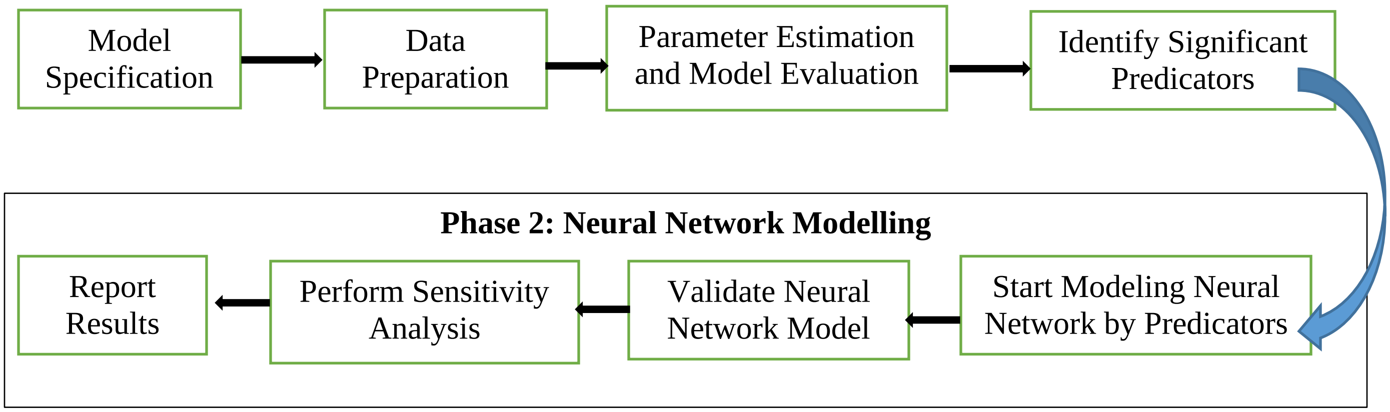

Figure 2: Research Methodology

All nine UTAUT model construct statements were measured through five point Likert scale from Strongly Agree to strongly disagree (5 =strongly agree, 4 = agree,, 3 = neutral, 2 = disagree =strongly disagree). A total of 24 construct statements were measured. The unbiasedness of the sample was ensured as there was no age and gender limitation enforced on the respondents.

3.2. Data Collection

The respondents of the study were private and public sector employees located in the Ethiopia. Employees from 21 public and 13 private organizations were included in the studies. The public sector includes the federal government of Ethiopia, public university employees, and other federal government organizations. The regional government public sectors include hospitals, regional institutions, and public government offices. The private sector includes industrial firms, private hospitals, colleges, and institutions. These organizations and institutions were selected since all provide mobile bases whistleblowing services. In addition, the government of Ethiopia encourages employees to blow the whistle for serious misconduct, either by an organization, authority or individual and reports to either internal or external parties through mobile-based whistleblowing services. All the respondents were above the age of 22 years or higher. Stratified sampling techniques were used where each private and public organization represents a stratum since each organization's whistleblowing culture may differ. A sample was then drawn from each stratum and a total of 689 employees were chosen for this study.

Following that, the sample size was proportionally distributed among the thirty-four strata based on the size of the population in each group. Data was gathered between December 2022 and January 2023.

4. Data analysis and results

4.1. Descriptive statistics of the sample

A total of 689 employees of private and public organizations, 312 (45.28 %) men, and 377 (54.72 %) women, responded to these study questionnaires. The survey includes people of every age, with 41.94% (or 289 respondents) in the 21–30 year age range, 42.38% (or 292 respondents) in the 31-40 year age range, and only 15.67% (or 108 respondents) in the 40–plus year age range. As shown in Table 1, 63.28 6% (i.e. 436 respondents) were from public organizations and 36.72% (253 respondents) were from private organizations.

Table 1: Actual Sample size per public and private sector organizations

Sector	Frequencies	Percentages
Public	436	63.28
Private	253	36.72

Table 2: General Demographic Information

Democratic		Frequencies	Percentages
Age	21 – 30	289	41.94
	31 – 40	292	42.38
	> 40	108	15.67
Gender	Male	312	45.28
	Female	377	54.72
Frequency of Internet Usage per Day	30 minutes - 1 hour	213	30.91
	1 - 4 hour	268	38.89
	5 - 8 hour	116	16.83
	9 - 12 hour	69	10.01
	13 - 16 hour	23	3.33
	17 - 20 hour	0	0
	> 20-hour	0	0
Frequency of Mobile Application usage per a week	Never Used	0	0
	1 - 5 times	227	32.9
	6 - 10 times	293	45
	11 - 15 times	112	16
	> 15 times	57	8.1
Educational Level	Illiterate	0	0
	Secondary School	38	5.5
	Diploma degree School	205	29.7
	BSc Degree	384	55.7
	Master Degree	59	8.5
	Ph.D. Degree	3	0.42

The interviewees had at least a secondary school certificate, and none of them were illiterate. The greater number of the respondents were BSc degree holders with 55.7% (384 respondents) and 29.7% (205 respondents) having Diploma degree School whereas only 8.5% (i.e. 59 respondents) have master's degrees. In addition, there were 3 Ph.D. holder respondents to our questionnaires.

The demographic information also contains the internet usage frequency in a single day. The result shows that all of the respondents are active in internet usage with 100% of the respondents accessing the internet from their workplace (organization) or at home for different purposes per day. 38.89 % (268 respondents) browsed the internet for one to four hours while 30.91% (213 respondents) browsed the internet in less than 1 hour. On the other hand, 16.83 % and 10.01% of the respondents were browsing the internet for five to eight hours per day and for nine to twelve hours per day respectively. However, 3.33% (23 respondents) were browsing the internet for thirteen to sixteen hours per day.

Additionally, we also gathered information on the number of times they used mobile-based applications for their day-to-day activities within a week. 45 % of the respondents used mobile-based applications 6 to 10 times a week whereas 32.9 % of the respondents used any mobile applications 1 to 5 times a week. The other 16 % of the respondents used mobile applications 11 to 15 times and the other 8.1% used more than 15 times a week. The finding indicates that there is a high number of mobile application usage for day-to-day activities. The demographic variables of the sample are summarized in Table 2.

4.2. Testing Constructs Normality

A normality test is essential to access and analyze the sample data with a non-normal distribution for the results of the specified nonlinear model to be valid. Prior studies (e.g. Bennet, Sankaranarayanan, & Babu, 2015) indicate that it is necessary to consider the use of parametric statistical tests. With the help of statistical tools such as the Pearson's Skewness and Kurtosis parameters, the normality of the data is examined. According to Sharma & Ojha (2020) Skewness is a statistical number that tells us if a distribution is symmetric or not whereas Kurtosis is a measure of whether the data are heavy-tailed or light-tailed relative to a normal distribution.

As Azzalini et al. (2014) indicated, these parameters should fall within the region of -2.58 to +2.58 and our study finding shows that each variable's value fell within the acceptable range and our data is normally distributed.

4.3. Confirmatory Factor Analysis (CFA)

Confirmatory factor analysis is a multivariate statistical technique that evaluates the degree to which the measured variables reflect the number of constructs and it helps in defining the degree of fit between the model's constructs and the data gathered (Alavi et al., 2020). In order to evaluate the assumptions, a two-step analysis was used, with the goal of first looking at the measurement model and then looking at how well the structural model fit. Convergent validity, discriminate validity, and construct reliability were evaluated in order to determine the goodness of fit. To calculate the necessary results, Confirmatory factor analysis was performed using AMOS 24 (Byrne, 2016).

Table 3: Correlation matrix of variables, Discriminant validity and Convergent Validity Results

VR	CR	AVE	MSV	MaxR (H)	EE	PE	SI	FC	BI	PPR	TR	PI	PSR	PInn
EE	0.901	0.721	0.565	0.923	0.789									
PE	0.832	0.690	0.565	0.978	0.756	0.745								
SI	0.813	0.683	0.454	0.977	0.325	0.296	0.812							
FC	0.789	0.586	0.523	0.984	0.731	0.542	0.231	0.799						
BI	0.835	0.641	0.426	0.923	0.654	0.631	0.254	0.548	0.831					
PPS	0.912	0.742	0.458	0.913	0.721	0.641	0.315	0.495	0.456	0.821				
TR	0.911	0.713	0.451	0.954	0.512	0.467	0.361	0.513	0.566	0.631	0.845			
PI	0.799	0.573	0.451	0.962	0.678	0.589	0.425	0.534	0.513	0.342	0.677	0.834		
PSR	0.882	0.791	0.533	0.952	0.662	0.612	0.460	0.683	0.632	0.456	0.753	0.653	0.823	
PInn	0.713	0.623	0.654	0.877	0.425	0.336	0.312	0.563	0.542	0.337	0.622	0.547	0457	0.822

Note: AVE: Average Variance Extracted, CR: Composite Reliability; MSV: Maximum Shared squared Variance; MaxR(H), Maximum Reliability, VR: Variable.

Convergent validity demonstrates whether a test that is intended to evaluate a specific construct correlates with other tests that do the same (Ljótsson et al., 2020; Byrne, 2016). In this research, Convergent validity was investigated using average variance extracted (AVE) and composite reliability (CR). As a general rule, AVE needs to be greater than 0.50 to be regarded as having good convergent validity and reliability (Skiendziel, Rösch & Schultheiss, 2019).

Discriminant validity studies whether concepts or measurements that aren't meant to be related are truly unrelated (Byrne, 2016; Skiendziel, Rösch & Schultheiss, 2019). It helps to validate the correlation of the respondents' answers to the survey items with the latent variables either lightly correlated or not correlated at all with other latent variables. The discriminant validity of each concept is confirmed by the values of Maximum Shared squared Variance being less than the values of average variance extracted (Ljótsson et al., 2020). Table 3 demonstrates that all composite reliabilities (CR) are greater than the threshold of 0.70, indicating that the models are distinct from one another. Additionally, Table 3 shows that the AVE for each concept is higher than the threshold of 0.50. Composite Reliabilities values exceeding AVE confirmed the convergence validity. AVE denotes numbers higher than the suggested default value of 0.50. As a result, all constructs' reliability is adequate.

4.4.1. Measurement Model Assessment

Using AMOS 24.0, the measurement model was analyzed and aids in the evaluation of the indicators that are used to verify the latent variables. The fit measures were calculated to evaluate how well the model matched the gathered data. The most common fit metrics used to assess the model fit indices includes the Goodness of Fit Index (GFI) = 0.94 which is a measure of fit between the hypothesized model and the observed covariance matrix. According to Byrne (2016) the model is acceptable if the Goodness of Fit Index exceeds 0.90. The Adjusted Goodness of Fit Index (AGFI) helps to adjust the value to the degrees of freedom in the model, is 0.92. The GFI and AGFI range between 0 and 1, with a value of over (Byrne, 2016). Normed Fit Index (NFI) which measure the incremental fit of the model is 0.95. NFI Ranges from 0 to 1, where 1 is a perfect fit and the model is regarded acceptable if the Normed Fit Index (NFI) exceeds 0.90 (Byrne, 2016).

The Root Mean Residual (RMR) which represents the square root of the difference between the residuals of the sample covariance matrix and the hypothesised covariance model is 0.03. RMR zero represents a perfect fit, but the maximum is unlimited. According to some researchers (Browne & Cudeck 1993; Stieger, 1990), RMS should be less than .08 and ideally less than .05. The Root Mean Square Error of Approximation (RMSEA) = 0.057 measures the fit of a proposed structural equation model to observed data (i.e. estimates the lack of fit in the proposed model compared to a perfect model) (Byrne, 2016). An RMSEA in the range of 0.05 to 0.10 was considered an indication of fair fit and values above 0.10 indicated poor fit (MacCallum et al, 1996). According to the results of the fit indices mentioned above, the fit indices result in acceptable model fit. As a result, the measurement model fits the data well.

4.5. Hypotheses Testing: Results of Structural Model

Different processes are used for the structural model evaluation, including evaluating the squared multiple correlations, checking the model fit indices, and examining the standardized path coefficients. Structural equation modeling (SEM) is a multivariate statistical analysis technique that is used to analyze structural relationships and to show the strength, significance, or insignificance of each path. The general guidelines applied in this structural evaluation are the same as those applied in measurement tests. The findings reveal that the general model, Chi-square ($\chi 2$) =769.56, degree of freedom (df =389), normed Chi-square ($\chi 2$/df) = 2.02, p-value <.001, suggests a good fit.

The normed Chi-square result of 2.02 suggests really quite excellent since it's below 3.0. As it is discussed in the previous section, the fit indexes including The Goodness of Fit Index (GFI), Adjusted Goodness of Fit Index (AGFI), Root Mean Residual (RMR), Normed Fit Index (NFI) are all above 0.90, and the RMSEA = 0.057 is below the cut-off point of 0.06 for statistical significance (Byrne, 2016). A total of nine hypotheses were examined in this research. The strength of each route is examined by the beta values, which show its weight (Al-Busaidi, 2012). The findings showed that the suggested study model satisfactorily explained a total variance in the behavioral intention of 72%. This shows the importance of variables like Personal Integrity, personal innovativeness, perceived privacy risk, perceived security risk, and trust in predicting an individual's intention to accept a whistleblowing mobile application. All the hypothesized relationships are supported as the path coefficients to be significant at $p < .05$ as shown in table 4.

Table 4: Hypotheses Results

Hypothesis	**Correlation**	**Estimate**	**S.E.**	**p-value**	**Outcome**
H1	PE →BI	0.311	0.061	0.002	Supported
H2	EE →BI	0.214	0.041	0.001	Supported
H3	EE →PE	0.012	0.021	0.112	Unsupported
H4	SI →BI	0.015	0.035	0.114	Unsupported
H5	FC →BI	0.146	0.046	0.074	Supported
H6	TR →BI	0.231	0.071	0.003	Supported
H7	PI →BI	0.168	0.056	0.050	Supported
H8	PI →PE	0.152	0.059	0.050	Supported
H9	PPR→BI	0.321	0.053	0.025	Supported
H10	PSR→BI	0.231	0.051	0.001	Supported
H11	PInn→BI	0.281	0.055	0.012	Supported

4.6. Artificial Neural Network (ANN) Approach

In this study, cutting-edge hybrid Structural Equation Modeling and Artificial Neural Network, a well-known machine learning tool, were used. The complexity of business decision-making makes it challenging to develop effective statistical models, such as multiple linear regression and structural equation modeling. ANN was initially created as incredibly simplified representations of the human nervous system that could learn, generalize, and extrapolate. Artificial Neural Networks are able to educate themselves in addition to accumulating, storing, and recognizing patterns of knowledge based on experience.

Finding both linear and nonlinear relationships between decision variables is one benefit of using neural networks in complicated business decision-making issues. There are numerous varieties of neural network models in the literature (Tino, Benuskova & Sperduti, 2015). In this study, we used the widely used feedforward back-propagation multilayer perceptron neural network model.

ANNs are mathematical and elaboration models that use a straightforward pattern of connected elements to solve complicated and non-linear problems by simulating the behavior of biological neurons ((Zhang & Zhang, 2018; Tino, Benuskova & Sperduti, 2015; Zou, Han, & So, 2009). The most significant characteristic of ANNs is their capacity for learning mathematical and statistical models through experience. In addition to linear relationships between independent and dependent factors, artificial neural network models are also capable of detecting nonlinear relationships (Zhang & Zhang, 2018).

Artificial neural network models have been used successfully to solve a variety of complex business problems, including pattern recognition (Abiodun et al., 2019), Credit card fraud detection (Asha & KR, 2021), nanophotonics (Zhang et al., 2019), mobile commerce (Hew et al., 2019), mobile learning (Leong et al., 2020), and acceptance of in healthcare technology (Shahid, Rappon & Berta, 2019).

4.6.1. Validations of Neural Networks

In this study, the most widely used statistical software package, SPSS 23, was utilized to carry out the ANN analysis. The PLS-SEM results' significant predictors are taken into account in ANN analysis. In order to explain neural networks and the variables that a user can control while training a neural network, the backpropagation multilayer perceptron neural network model was used (Hong, 2015). In order to prevent ANN models from overfitting, a ten-fold cross-validation approach was used with a ratio of 10:90 for both training and testing data, respectively. In this study, we have divided data into 10 equal groups. A total of 10 nodes were used in a neural network model and a Root Mean Square of Error (RMSE) was used to assess the Neural Network model's predictive accuracy.

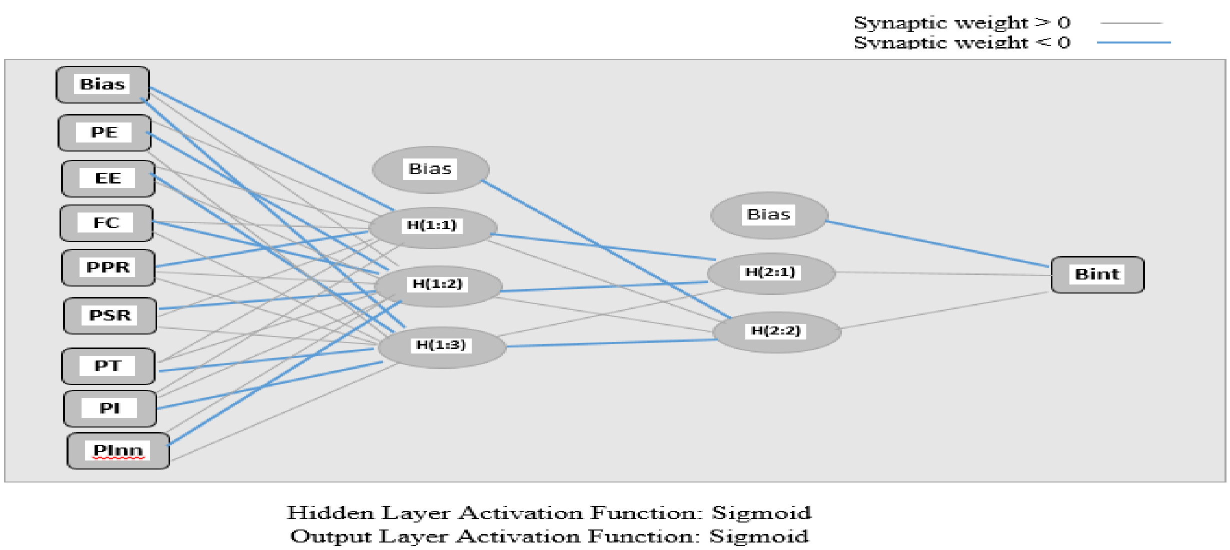

Figure 3. Deep Artificial Neural Network Model for the intention to adopt whistleblowing mobile application

Due to a lot of endogenous constructs, this research solely concentrates on behavioral intention, which has the maximum number of predictors; as a result, there will only be one deep ANN model. As shown in Figure 3, The ANN model consists one output neuron, which represents the dependent variable (acceptability of whistleblowing mobile applications) and numerous input neurons with significant indicators to behavioural intention such as performance expectancy, effort expectancy, social influence, facilitating conditions, trust, personal integrity, personal innovativeness, perceived privacy risk and perceived security risk. Two-hidden layer deep ANN architecture was employed with an aim to allow deeper learning to take place for each of the output neuron node and represent a continuous function. In this research, the sigmoid function is used as the activation function for both output and hidden neurons. Several studies recommended Root mean square of errors (RMSE) for the accuracy of neural network models. Table 5 provides a summary of the RMSE values of ANN model for the training and testing data of this study. The RMSE values vary from 0.079 to 0.124 for the training data and 0.098 to 0.156 for the testing data. Because of the extremely small values and variations in RMSE (i.e. average RMSE for training model as 0.098 and average RMSE for testing model as 0.108) and standard deviation for both the training and testing data, we can predict that the proposed researcher model will have higher accuracy with ANN suggested by prior research (Liébana-Cabanillas et al., 2017).

Table 5: RMSE Values for Neural Network Validation.

Artificial Neural Network	**RMSE value for Training**	**RMSE value for Testing**
ANN1	0.101	0.112
ANN2	0.082	0.098
ANN3	0.121	0.156
ANN4	0.111	0.142
ANN5	0.079	0.094
ANN6	0.085	0.099
ANN7	0.124	0.154
ANN8	0.091	0.101
ANN9	0.114	0.141
ANN10	0.112	0.132
Average	0.099	0.119
Standard Deviation	0.016	0.024

4.6.2. Sensitivity Analysis

According to Liébana-Cabanillas et al. (2017), the significance of independent variables in determining whether or not to accept whistleblowing mobile applications is a measure of variation in the prediction of different values of independent variables. Normalized importance is simply the importance values of each independent variables divided by the largest importance values or the mean of each predictor is used against the highest mean value, expressed in percentage. Details on the mean importance and normalized relevance of each predictor used in ANN modeling are shown in Table 6.

Table 6: Sensitivity Analysis (Independent variable importance).

	PE	**EE**	**FC**	**PT**	**PPR**	**PSR**	**PInn**	**PI**
ANN1	0.231	0.134	0.134	0.284	0.291	0.221	0.278	0.232
ANN2	0.314	0.122	0.19	0.198	0.301	0.198	0.145	0.298
ANN3	0.308	0.183	0.123	0.256	0.289	0.199	0.131	0.211
ANN4	0.288	0.124	0.198	0.274	0.232	0.185	0.117	0.176
ANN5	0.412	0.174	0.188	0.341	0.389	0.231	0.118	0.241
ANN6	0.342	0.165	0.199	0.296	0.401	0.258	0.156	0.275
ANN7	0.221	0.231	0.214	0.264	0.234	0.163	0.121	0.184
ANN8	0.342	0.189	0.134	0.301	0.261	0.134	0.131	0.234
ANN9	0.311	0.199	0.147	0.322	0.233	0.197	0.145	0.188
ANN10	0.289	0.122	0.133	0.342	0.321	0.214	0.112	0.223
Mean	0.306	0.164	0.166	0.288	0.295	0.212	0.145	0.211
Standard Deviation	0.055	0.038	0.035	0.043	0.061	0.035	0.049	0.042
Relative Importance %	100	53.59	54.25	94.12	96.41	65.36	47.38	
Ranking	1	5	6	3	2	4	7	

As shown in Table 6, the result of the neural network sensitivity analysis displays that performance expectancy is the most vital predictor of behavioural intention to use whistleblowing mobile application followed by Personal Integrity, personal innovativeness, perceived privacy risk, perceived security risk, and trust. Additionally, Personal innovativeness was found to be the least predictor to develop the behavioural intention among Ethiopians for the adoption of whistleblowing mobile application. Furthermore, it is noteworthy that the most important variable in determining behavioural intention to whistleblowing mobile application is performance expectancy. However, structural equation modeling (SEM) results revealed that perceived privacy risk was the most significant predictor of intention to use whistleblowing mobile application. The difference result by SEM modeling and Neural Network Modeling can be validated by the n nonlinear and non-compensatory nature of neural network model and better predictive accuracy of the later model.

5. Discussion

In the current digital world, organizations' whistleblowing services are mainly dependent on different types of digital platforms to enable employees to anonymously report fraud or criminal activity in the workplace. This helps to achieve greater participation and awareness, a higher level of trust, and deeper engagement of employees and stakeholders. Additionally, providing an effective whistleblowing reporting channel for reporting illegal or unethical activities will help to build an ethical corporate culture as well as trust both inside and outside the organization. Delivering whistleblowing services to people who reside in remote areas of the organization has long been a problem for the organization management.

Utilizing whistleblowing mobile applications may help overcome obstacles to reporting illegal or unethical activities and provide an efficient means of delivering whistleblowing services. Based on our analysis and survey results collected from private and public organizations in Ethiopia, employees are eager to adopt and utilize a whistleblowing mobile application. This research analyzes the impact of eight factors on the intention to use the whistleblowing mobile application in both private and public organizations in Ethiopia.

The use of whistleblowing mobile applications by employees was found to be influenced by seven out of the eight parameters. In particular, it was discovered that factors such as performance expectancy, perceived privacy risk, trust, perceived security risk, effort expectancy, personal integrity, personal innovativeness, and facilitation conditions affected the employees' decision to use whistleblowing mobile applications. According to the statistical findings, the suggested model was successful in achieving an acceptable level with respect to the predictive power of the dependent variable i.e. behavioral intention towards whistleblowing mobile applications.

In this study, the structural models were examined both with and without the addition of the extra variables of Personal Integrity, personal innovativeness, perceived privacy risk, perceived security risk, and trust. In line with expectations, the UTAUT's R2 was 56% before rising to 72% upon the addition of the previously mentioned four components. As a result, the proposed study model's predictive potential has risen with the addition of new elements.

The findings show that employees' behavioral intentions toward the new technology are primarily determined by their perceived privacy risk in whistleblowing mobile applications. In this regard, employees of organizations are expected to use whistleblowing mobile applications to submit a whistleblowing report anonymously without revealing their identity. Whistleblowers are very conscious about their personal information. They need an assurance for their personal information is not at risk (i.e. unauthorized use and shared to third parties without their consent while using whistleblowing mobile applications).

The performance expectancy, according to the findings, is the second most important factor affecting employees' intentions to use whistleblowing mobile applications. It is noteworthy that the neural network results show that performance expectancy is the main predictor of behavioral intention. This result may have been caused by the better predicted accuracy of the proposed neural network models. The performance expectancy are the main consideration for employees in Ethiopian organization when deciding whether to adopt whistleblowing mobile applications. Therefore, organizations can improve their whistleblowing services by showcasing and publicizing their most valuable aspects. According to different studies (Alalwan et al., 2017; Abbasi et al., 2021), performance expectancy is one of the most important indicators of a person's behavioral intention.

Furthermore, this study reveals that perceived security risk is one of the factor for behavioral intention to use whistleblowing mobile applications. Ethiopians are conscious on the protection of information and chances of hacking and security breaches associated with whistleblowing mobile applications usage. Prior studies (Biletskyi, 2022) also indicated security issues is one of the most important factors in utilization of technological whistleblowing services.

Another significant factor that affects users' intention to utilize whistleblowing mobile applications is perceived effort expectancy and trust. This research demonstrates that Ethiopian organization employee's citizens prefer to submit a whistleblowing report without revealing their identity and obtain up-to-date information about organization whistleblowing services through mobile applications since it is simple to use and takes less time and effort than other antiquated ways. According to whistleblowing research (walle, 2020), whistleblowers prefer to communicate anonymously. Allowing people to remain anonymous while voicing concerns will aid in the development of trust and confidence in whistleblowing mobile applications. In summary, provision of anonyms reporting channel and updated quality information encourage users to adopt whistleblowing mobile applications. This finding is in line with earlier research (Alalwan et al., 2017; Abbasi et al., 2021), which showed that lack of trust is a significant obstacle to accepting and utilizing new systems or technologies.

The majority of the UTAUT-based investigations have established a statistically significant link between expected expectancy and behavioral intention (Zhou et al., 2019; Leong et al., 2020). According to this study findings, there is no correlation between social influence and behavioral intention, suggesting that employees of an organization in Ethiopia are least likely to suggest that their family and friends use whistleblowing mobile applications. Furthermore, the result indicates that facilitating conditions have a favorable impact on behavioral intentions to utilize whistleblowing mobile applications. Employees of an orgnaization gives very conscious of the resources at their disposal, the necessary knowledge, and the facilities to access and utilize whistleblowing mobile applications. This includes good internet connection, smartphone and excellent whistleblowing mobile application. The result is in line with previous studies in information system domains (Sharma et al., 2018; Abbasi et al., 2021).

At last, the findings revealed a strong and favorable correlation between personal integrity and behavioral intention to use whistleblowing mobile applications. Since whistleblowers are frequently driven by their own sense of morality and a sincere desire to safeguard the public, personal integrity play a vital role in the adoption of whistleblowing mobile applications.

5.1. Theoretical Implications

This research offers an array of insightful findings for researchers. First, to describe the behavioral intention towards whistleblowing mobile applications, it has first expanded the existing research by including five new elements, namely Personal Integrity, personal innovativeness, perceived privacy risk, perceived security risk, and trust, into the UTAUT model. This is adds more knowledge in digital government, mobile government adoption specifically to whistleblowing system studies. Second, application of the structural equation modelling to neural network modeling that which offers a comprehensive understanding. Using neural network modeling, this study created a non-compensatory model to forecast employees of Ethiopian organizations behavioral intentions toward whistleblowing mobile applications in an effort to solve one of the flaws in various previous studies on technology adoption. Thus, the neural network modeling was used to prioritize significant independent constructs and validate structural equation modelling results. Third, the finding of this study add to existing research on the use of mobile technology in whistleblowing services. Lastly, this study offers significant research findings by investigating the acceptance of whistleblowing mobile applications for whistleblowing services in context of developing country like Ethiopia.

5.2 Implications for practice

The statistical evidence discovered in this work has significant implications from a practical standpoint. The findings of this study will help organizations to create methods that can encourage employees to use whistleblowing mobile application to blow the whistle in a fight against unlawful activities by emphasizing ways to make the whistleblowing process more useful, simple, pleasurable, and reliable. The study reveals that namely Personal Integrity, personal innovativeness, perceived privacy risk, perceived security risk, and trust have an important role. Hence, organizations must keep these constructs in focus when they are developing whistleblowing mobile application. In addition, this result will help both private and public organizations of Ethiopian to develop a suitable whistleblowing strategies and polices to encourage employees to use whistleblowing mobile applications.

As perceived privacy risk, performance expectancy and trust are the most significant variables influencing the decision to accept the whistleblowing mobile applications services, Organizations enhance the quality of the application by delivering secured, reliable and efficient services. The study also validated the impact of perceived security risk, effort expectancy on behavioral intention. Employees place a high value on using the secure whistleblowing application, which runs smoothly with little effort. As a result, it is advised that whistleblowing mobile application developers for organizations whistleblowing services focus more on service security and simplifying the requirements for using and exploring mobile applications.

Furthermore, the strong association between perceived privacy risk and behavioral intentions toward whistleblowing mobile applications suggests that employees give security and privacy measures quite higher priority when using whistleblowing services on mobile devices. To reduce the risks associated with using whistleblowing mobile applications, application developers and system analysts should focus more on creating robust and secure application. This can be done by implementing an additional layer of protection.

6. Conclusion and Limitation

The development of technologically enabled whistleblowing services has changed the whistleblowing process, which is now more widely acknowledged as a key tool in the discovery and prevention of corruption and other wrongdoing. The main aim of this study was to explore the factors influencing the employee's behavioral intention to use whistleblowing mobile applications in Ethiopian public and private organizations. The findings show that namely Personal Integrity, personal innovativeness, perceived privacy risk, perceived security risk, and trust have a positive influence on user's behavioral intention to use whistleblowing mobile applications. The results also show that social influence had no effect on behavioral intention, this implies that, in terms of using whistleblowing mobile applications, employees cannot be affected by the views of other people. This shows that employees in Ethiopian organizations are expected to use whistleblowing mobile application because of its usefulness and simplicity of use. The findings of this study will assist firms in creating effective strategies to encourage employees to use mobile applications for whistleblowing services.

This study has a minor limitations. First, the study is cross-sectional but it is recommended to conduct longitudinal study to comprehend user's intention on the progressive changes. Second, this study mainly conducted in Ethiopia. As a result, it is impossible to generalize the model to other countries, and it is advised that cross-cultural research be done to determine whether the concept applies to other developed and developing countries.

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