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Integrating UTAUT and social exchange theory to decipher knowledge-sharing in crowdsourcing

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Microtask crowdsourcing platforms enable rapid, large-scale completion of simple tasks by a globally distributed workforce. This study investigates the factors influencing knowledge-sharing behaviours among crowdworkers, integrating the Unified Theory of Acceptance and Use of Technology (UTAUT) with Social Exchange Theory (SET) to provide a comprehensive understanding of these dynamics. Using Structural Equation Modelling (SEM) to analyse survey data from 413 crowdworkers, the study identifies key drivers such as Performance Expectancy (PE), Effort Expectancy (EE), and Rewards, which significantly impact both Knowledge-sharing Intention (KSI) and Behaviour (KSB). Our findings highlight the importance of user-friendly and accessible digital tools in promoting active knowledge-sharing within online communities. Effort Expectancy directly influences Knowledge-sharing Behaviour, highlighting the importance of usability in sustaining platform adoption. This research confirms the robustness of the UTAUT model and extends it with social exchange elements to offer new insights into human aspects of information systems.

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Introduction

Crowdsourcing represents an innovative work model in today's digital era, characterised by a dynamic and diverse community of crowdworkers who perform microtasks, known as Human Intelligence Tasks (HITs), on crowdwork platforms like MTurk, Prolific, and Appen. These tasks range from market research and media annotation to data entry and surveys, creating a unique ecosystem where collective intelligence and individual skills combine to facilitate task completion and innovation (Gadiraju et al. 2014; Liang et al. 2022).

Despite the isolating nature of many crowdwork platforms, crowdworkers develop robust self-organised communities outside these platforms, leveraging forums and social apps. These communities allow crowdworkers to share opportunities and improve efficiency using scripting tools like HIT catchers. Often, the aim is to counter unfair practices and improve working conditions (Irani 2015; LaPlante and Silberman 2016; Brawley and Pury 2016; El Maarry et al. 2018; Gerber 2021). Meanwhile, such knowledge-sharing entails sharing technical know-how and work strategies, which in turn becomes crucial for better and more efficient handling of HITs and can ultimately help crowdworkers maintain a competitive edge in a swiftly evolving digital marketplace. While extensive research has examined the general conditions of crowdwork (Gray et al. 2016; LaPlante and Silberman 2016; Brawley and Pury 2016; Osterbrink and Alpar 2021), relatively little is known about how technological tools, such as HIT catchers, influence crowdworkers' knowledge-sharing behaviour.

To bridge this gap, our study investigates the dynamics of knowledge-sharing among crowdworkers. Specifically, we aim to identify the primary motivations driving crowdworkers' knowledge-sharing behaviour within their communities and examine how technology-related and social interaction factors influence these behaviours. Addressing this issue is crucial, as earlier research indicates significant disparities in work opportunities and outcomes between technologically proficient and less experienced crowdworkers. Experienced, tech-savvy crowdworkers are better equipped to use HIT catcher tools, enhancing task completion rates and income (Difallah et al. 2012; Martin et al. 2014). Conversely, less proficient crowdworkers often lack awareness or capability in utilising such tools, resulting in unequal job opportunities, lower productivity, and reduced income (Xie et al. 2023). We posit that knowledge-sharing can mitigate these discrepancies by creating equitable opportunities, enhance collective efficiency, and foster innovation within the crowdsourcing ecosystem.

To achieve these objectives, we integrate the Unified Theory of Acceptance and Use of Technology (UTAUT) and Social Exchange Theory (SET) to address both motivational drivers and technology-mediated behaviours in crowdworkers' knowledge sharing. This theoretical pairing bridges the psychological underpinnings of sustained knowledge exchange (via SET) and the technological facilitators shaping such behaviour (via UTAUT). Specifically, SET provides a comprehensive lens to evaluate intrinsic and extrinsic motivations, such as reciprocity, trust, and perceived rewards, which sustain knowledge sharing beyond short-term interactions. By emphasising relational dynamics over time, SET clarifies why individuals engage in and persist with knowledge-sharing practices (Peng 2024). Meanwhile, UTAUT offers a validated framework to assess how technology-specific factors, including perceived usability, effort expectancy, and social influence, shape the adoption and sustained use of digital platforms (Angosto et al. 2023), inherently crucial to crowdworkers' interactions. Together, these theories address complementary facets of our research context.

The remainder of this paper is structured as follows: Section 2 discusses the theoretical background and introduces our research hypotheses on factors influencing crowdworkers' knowledge-sharing behaviours. Subsequently, we outline our methodological approach, detailing our questionnaire-based survey of 413 MTurk crowdworkers, and the subsequent data analysis employing partial least squares structural equation modelling (PLS-SEM). We then present our results, highlighting the significant roles of Performance Expectancy, Effort Expectancy, and Rewards on Knowledge Sharing Intention and Behaviour.

Theoretical background

In this research, we integrate two influential theoretical frameworks, Social Exchange Theory (SET) (Blau 2017) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al. 2016), to explore crowdworkers' knowledge-sharing behaviours. This integrated approach emphasises intrinsic and extrinsic motivations, as wel as technological factors that may either facilitate or impede such behaviour.

First, SET posits that social interactions involve exchanging tangible or intangible resources (Ahmad et al. 2023). SET is characterized not as a single theory, but rather a broad conceptual paradigm comprising various models (Cropanzano et al. 2017). A common element across these SET-inspired models is the principle of reciprocity, where exchanges are driven by mutual expectations of benefits. Reciprocity motivates individuals to share knowledge, anticipating similar future contributions from others. These anticipated rewards can be intrinsic, driven by psychological satisfaction and personal traits like openness and altruism (LaPlante and Silberman 2016; Brawley and Pury 2016; Osterbrink and Alpar 2021), or extrinsic, encompassing external rewards such as community reputation (Maharani 2017; Deng and Guo 2018; Fang and Zhang 2019; Luo et al. 2021).

Further, collaboration significantly influences knowledge-sharing behaviour (Sawan, Suryadi (2021); Ng 2023). A culture emphasising trust, shared goals, and innovation fosters an environment conducive to knowledge sharing, even in decentralised settings like crowdsourcing. Trust, though not explicitly stated in SET, remains implicitly central, as reciprocal exchanges presuppose trust among participants (Cropanzano and Mitchell 2005). Trust encourages more open exchanges of ideas and expertise, crucial in virtual communities where interactions occur among loosely connected individuals without institutional mandates (Wang and Kim 2024). Therefore, SET highlights how reciprocal benefits and social relationships motivate knowledge-sharing in virtual communities (Yoshikawa et al. 2018; Luo et al. 2021).

The Unified Theory of Acceptance and Use of Technology (UTAUT) is another influential research model that explains technology acceptance and use, focusing on several factors such as performance expectancy, effort expectancy, social norms and facilitating conditions (Onaolapo and Oyewole 2018; Angosto et al. 2023). UTAUT has been applied within the knowledge sharing domain as well, given the significant role of digital platforms and technological features in facilitating online interactions (Kazemian and Grant 2023).

Previous studies have explored knowledge-sharing in various contexts using frameworks such as SET and UTAUT, offering valuable insights into the interplay of social and technological factors that shape knowledge-sharing behaviours. For example, Kazemian and Grant (2023) explored the antecedents and outcomes of enterprise social network usage in UK higher education, utilizing the UTAUT framework to examine the role of organisational culture, trust, and perceived usefulness in driving adoption. Similarly, Almujally and Joy (2018) extended the UTAUT framework to investigate the adoption of web-based knowledge-sharing systems in Saudi universities. Their study highlights factors like performance expectancy and social influence, but their focus on institutional knowledge-sharing systems remains within the context of centralised participation. Other researchers have employed SET to explore social mechanisms underpinning knowledge-sharing. For instance, Zhao and Detlor (2023) investigate knowledge-sharing within virtual communities, emphasizing the interaction between social norms and generalized trust from Social Capital Theory and costs and benefits from Social Exchange Theory. Similarly, Zhu et al. (2023) examine knowledge-sharing in enterprise social media platforms, focusing on trust mechanisms like affect-based trust and motivations such as reciprocity.

The above studies, while informative in terms of online knowledge-sharing, their primary focus diverges from crowdsourcing platforms. In contrast, our research specifically focuses on knowledge-sharing in crowdsourcing, integrating SET and UTAUT to provide a comprehensive analysis of both social and technological factors influencing knowledge-sharing among crowdworkers. This approach bridges the gap between existing research on general knowledge-sharing mechanisms and the unique challenges of crowdsourcing platforms, which involve decentralised, large-scale public participation, and which are often overlooked in existing literature.

In what follows we review prior literature utilising SET and the UTAUT, specifically emphasising factors and their interrelationships relevant to knowledge sharing behaviour. This review further supports and explains the development of our research hypotheses.

Research model and hypotheses development

In this study, the UTAUT model and Social Exchange Theory (SET) were integrated to investigate online knowledge-sharing among crowdworkers. UTAUT explores technology adoption, suitable here because crowdworkers rely on communication technologies. SET adds a social psychological perspective, focusing on costs, benefits, and social exchanges in knowledge-sharing. The integration of these two theories is shown in Fig. 1, the final theoretical model includes ten exogenous factors from SET and UTAUT, and two endogenous factors: knowledge-sharing intention (KSI) and behaviour (KSB). In what follows we develop our research hypotheses.

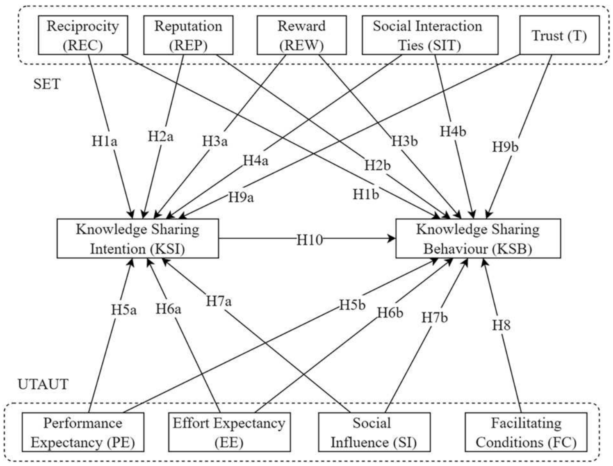

Fig. 1 Research model. The integrated theoretical model combining constructs from the Unified Theory of Acceptance and Use of Technology (UTAUT) and Social Exchange Theory (SET) to examine knowledge-sharing among crowdworkers. Hypothesised paths between constructs are labelled H1a–H10.

Reciprocity. Social exchange entails, as earlier highlighted some kind of reciprocity between involved parties. Here, reciprocity in crowdworkers' knowledge-sharing refers to the expectation that their contributions will be reciprocated, fostering a cycle of exchange (Nguyen 2021). This dynamic involves direct rewards and a sense of obligation, enhancing participation and mutual benefits within the community (Adamseged and Hong 2018). For reciprocity to be effective, it must be supported by trust—participants need to believe their contributions will be reciprocated with equally valuable inputs. Trust builds commitment and a supportive environment, while unmet expectations can undermine confidence and obstruct knowledge-sharing (Alwahdani 2019). Based on these considerations, the following hypotheses are proposed:

H1a: Reciprocity has a positive effect on the crowdworkers' intention to share knowledge.

H1b: Reciprocity has a positive effect on the crowdworkers' knowledge-sharing behaviour.

Reputation. Research shows that individuals may share knowledge within a group to enhance their professional reputation (Chang and Chuang 2011). Sharing knowledge helps them gain peer respect and be recognised as experts (Gang and Ravichandran 2015). When members believe that sharing will enhance their reputation, they are likely to continue this behaviour (Jiarui et al. 2022). This aligns well with the underpinning premise of SET, whereby social exchanges occur on the basis of motivations and rewards, whereby it can be argued that reputation can be one such reward. Naturally, whether this does indeed happen depends on the community's ability to recognise and value these contributions. This study explores crowdworkers' perceptions of how their knowledge-sharing activities influence their reputation. Therefore, the following hypotheses are proposed regarding reputation in crowdsourcing:

H2a: Reputation has a positive effect on the crowdworkers' intention to share knowledge.

H2b: Reputation has a positive effect on the crowdworkers' knowledge-sharing behaviour.

Reward. Directly drawing from SET, reward systems in virtual communities effectively motivate users to share knowledge for both extrinsic and intrinsic benefits. Tangible rewards like money or vouchers and virtual rewards such as badges and rankings encourage continuous content contribution (Anderson et al. 2013; Wei et al. 2015). For instance, the Mturk Forum[1] awards a 'Turker of the Month' based on votes and contributions, providing monetary incentives through PayPal to foster active participation.

Research also shows that intangible rewards, such as the satisfaction and enjoyment derived from helping others, significantly enhance knowledge-sharing (Fang and Zhang 2019; Cahyaningrum 2023). In this study, satisfaction and enjoyment are considered intrinsic motivators within the social exchange theory framework, viewed as positive outcomes from interactive behaviours (Osterbrink and Alpar 2021; Abdou et al. 2022). Additionally, acquiring knowledge through exchange is itself rewarding, contributing further to engagement in sharing activities (Ahuja 2020).

Based on these insights, the following hypotheses are proposed regarding the rewards' impact on crowdworkers' sharing behaviours:

H3a: Rewards have a positive effect on the crowdworkers' intention to share knowledge.

H3b: Rewards have a positive effect on the crowdworkers' knowledge-sharing behaviour.

Social interaction ties. SET necessitates by definition that social exchanges occur between two or more parties, whereby interpersonal relationships between them will influence whether behaviour will be reciprocated or not and how (Cropanzano et al. 2017). Against this context, earlier studies have found that if there are close social relationships between members within a virtual community, their online knowledge-sharing behaviours will be significantly enhanced (Wang et al., (2022a)). One explanation is that if community members connect with more people, they can access more relational resources, which can help themselves to get help from others in the future (Nguyen 2021). This study hypothesises that in the crowdworkers group:

H4a: Social Interaction Ties (SIT) have a positive effect on the crowdworkers' intention to share knowledge.

H4b: Social Interaction Ties (SIT) have a positive effect on the crowdworkers' knowledge-sharing behaviour.

Performance expectancy. Performance Expectancy (PE) refers to a user's expectation of the benefits and utility derived from using a specific technology (Hassaan et al. 2023). PE encompasses observed items such as usefulness, effectiveness, perceived speed, and relative advantage (Onaolapo and Oyewole 2018). Usefulness measures how the technology aids in knowledge-sharing activities (Nguyen 2021), effectiveness gauges whether the technology achieves its intended purpose, perceived speed assesses how quickly the technology operates, and relative advantage evaluates the benefits of the technology compared to alternatives, like time efficiency or performance improvement. These components form the basis for the hypotheses related to PE:

H5a: crowdworkers' Performance Expectancy has a positive effect on knowledge-sharing intention.

H5b: crowdworkers' Performance Expectancy has a positive effect on knowledge-sharing behaviour.

Effort Expectancy. EE as a latent variable contains the observed item perceived ease of use (Hung et al. 2019). This study chooses four observed items to measure EE: ease to use technology, ease to access technology, ease to learn technology and technical barriers (Onaolapo and Oyewole 2018). As a motivation for knowledge-sharing behaviour, perceived ease of use emphasises individuals' perceptions of the ease of using technology for knowledge-sharing (Lee et al. 2021). Technical barriers mainly involve the technical problems and challenges of using new technologies, such as lack of access to tutorial. Hypotheses for EE include:

H6a: crowdworkers' Effort Expectancy has a positive effect on knowledge-sharing intention.

H6b: crowdworkers' Effort Expectancy has a positive effect on knowledge-sharing behaviour.

Social Influence. As one key construct of SI, subjective norms are external stimuli from the social group that influence individual behaviour (Stok et al. 2015). Social norms arise from the willingness of groups to conform to specific shared expectations (Tesar 2020). Specifically, official attitudes and policies regarding knowledge-sharing create social norms that encourage or discourage this behaviour, which in turn affects employees' motivation to share knowledge. Group behaviour further reinforces this social norm and allows individuals to perceive this social pressure through the workplace climate (Nguyen 2021). Previous studies show subjective norms are important predictors of behavioural intentions in KS (Dong et al. 2022; Wu et al. 2023). The hypotheses regarding SI are:

H7a: crowdworkers' Social Influence regarding knowledge-sharing has a positive effect on knowledge-sharing intention.

H7b: crowdworkers' Social Influence regarding knowledge-sharing has a positive effect on knowledge-sharing behaviour.

Facilitating conditions. Facilitating conditions are crucial for technology adoption, as seen in digital banking (Nepal and Nepal 2023). Central to the concept of facilitating conditions, as elaborated in the Theory of Planned Behaviour, is the idea of perceived behaviour control. This refers to an individual's perceptions regarding the ease or difficulty of performing a given behaviour, which often involves assessing potential obstacles or supports (Liu et al. 2023).

In the context of virtual communities and microtask crowdsourcing, the role facilitating conditions play in enhancing knowledge-sharing among crowdworkers needs to be investigated. Therefore, we hypothesise that:

H8: Facilitating Conditions have a positive effect on the knowledge-sharing behaviour of crowdworkers.

Trust. Trust is a crucial factor in facilitating online knowledge-sharing (Ismail et al. 2019), and social exchanges and interactions. Based on SET, positive or otherwise benevolent actions increase trust and therefore promote positive responses and reciprocity (Cropanzano et al. 2017). As trust increases, individuals perceive less uncertainty and more security, making them more willing to share knowledge (Nguyen 2021). In virtual communities, members often lack basic trust due to unfamiliarity with each other (Wu et al. 2010). Without trust, initiating knowledge-sharing is difficult as contributors cannot predict others' responses (Li et al. 2023). Trust can mitigate this uncertainty, promoting knowledge-sharing and maintaining exchange relationships. Therefore, sufficient trust between knowledge providers and seekers is essential for peer communication among crowdworkers. This study hypothesises that:

H9a: Trust has a positive effect on the crowdworkers' intention to share knowledge.

H9b: Trust has a positive effect on the crowdworkers' knowledge-sharing behaviour.

Knowledge-sharing Intention. According to UTAUT, Behaviour Intention (BI) influences actual behaviour and has been widely researched (Chen et al. 2023). Knowledge-sharing intentions reflect the effort individuals are willing to invest in performing the behaviour (Dey and Mukhopadhyay 2018). This is similar to attitudes towards behaviour in TRA, TPB, and DTPB, as well as extrinsic and intrinsic motivation (Lakhal et al. 2013).

In this study, knowledge-sharing intention (KSI) indicates the degree to which a crowdworker believes they will share knowledge with peers. Here we hypothesise the effect of KSI on behaviour:

H10: Knowledge-sharing intentions of crowdworkers have a positive effect on their behaviour to share knowledge.

Methods

Sampling method. This study's sample was drawn from active crowdworkers on the MTurk microtasking platform. The survey was conducted in August 2023 by deploying six groups of 100 HITs each, without imposing a minimum HIT approval rate. This survey did not set a minimum HIT approval rate requirement to avoid response bias that could arise from only allowing workers with high approval rates to participate. This approach included individuals with lower approval rates, offering a broader understanding of the active MTurk population.

Although this study could not implement fair probability sampling, we attempted to enhance the fairness of the sampling survey by distributing multiple HIT groups on different days within the week. This method, a form of non-probability sampling known as convenience sampling, is particularly suitable for scenarios like this study, where the population is defined by participation in a specific online environment, and no specific inclusion criteria are imposed.

Instrument development and data collection. We developed a structured questionnaire to assess factors from our modified SET and UTAUT models, focusing on crowdworkers' demographic data and their perceptions related to knowledge-sharing. Key areas included the influence of reciprocity, reputation, and rewards on their willingness to share knowledge and the effects on their behaviour. By evaluating how these factors impact the community dynamics and personal incentives, we aligned our data collection directly with the research objectives.

Table 1 illustrates the survey questions regarding UTAUT and SET-related constructs. In the worker perception section, questions on Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC) from UTAUT were addressed separately. Latent variables such as PE and EE were decomposed into multiple indicators, and participants were prompted to explain challenges in accessing/sharing knowledge (e.g., perceived inefficacy). To enhance clarity, key terms like "sharing tools" were annotated with examples (e.g., forums like MTurk Crowd, Slack channels like Turker Nation, browser extensions like TurkerViewJS for rating HITs). Questions were adapted from prior research and contextualized to crowdworkers' skill-based knowledge sharing via communication tools. For example, the factor of social norms was adapted to measure platform and peer expectations and attitudes toward both, whereby that of Facilitating Conditions was adapted to assess technology integration, community/technical support, and compatibility with users' work styles (Ajzen 2020). These adaptations ensured alignment with the study's focus on collaborative knowledge dynamics among crowdworkers.

We also included age, gender, education level, and monthly income as control variables to account for potential effects on knowledge-sharing intention (KSI) and behaviour (KSB).

We evaluated the questionnaire's construct validity and reliability by deploying it on MTurk, where 20 crowdworkers provided feedback on knowledge-sharing behaviour. The questionnaire included 15 sections with 54 questions, segmented by Socio-demographic Background, Crowdwork Experience, HIT Preference, and Knowledge-sharing (KS) Behaviours, among others. Participants assessed item relevance and suggested improvements, ensuring alignment with category constructs. The instrument underwent six pilot rounds with the target demographic to enhance question clarity, flow, and accuracy, requiring approximately 10–15 minutes to complete, whereby during the sixth round, no more suggestions for improvements emerged and the questionnaire form and content stabilised.

A total of 454 valid samples were collected after removing 296 invalid responses based on attention check questions. After removing the missing data including participants who claimed not to have shared skill-based knowledge, a total of 413 samples were applied for SEM analysis.

Findings

Social-demographic background. Table 2 is a summary of demographic information of the participants. It is revealed that 57.5% are male and 40.1% are female. Most participants are aged from 25 to 44. In terms of education, more than a half of them are Bachelors.

Regarding the income, less than a quarter of the participants earn more than $501 per month, with around 3.4% of workers earning more than $5,000. Possibly benefiting from the increase in overall crowdsourcing industry revenues in recent years, this value has been better than the statistics of El Maarry et al. (2018). However, most of the workers still earn no more than $500 per month from MTurk.

From Table 2 it can be revealed that more than a quarter of the overall participants have a HIT approval rate lower than 97.5%, and more than 10% of the whole sample have a HIT approval rate lower than 95%. However, it is common for requesters to set this approval rate above 95–98% when posting HITs (Burnette et al. 2022; Hauser and Schwarz 2016; Kennedy et al. 2020; Saravanos et al. 2021). This means that many crowdworkers who are actively looking for HITs are losing out because of low HIT approval rates.

Measurement model evaluation

Normal distribution test. Tests for normal distribution were carried out using measures of skewness and kurtosis (Table 3). Values for kurtosis and skewness below 2.58 suggest normal distribution of data, with skewness above 3 indicating extreme skewness. Our sample size of 413 helped mitigate the effects of any non-normality on statistical analysis, confirming the data's adequacy for further processing (Hair et al. 2011).

Multicollinearity test. In Table 4, we show the results on multicollinearity through the Variance Inflation Factor (VIF), identifying no significant issues as all VIF values were well below the critical value of 5, indicating minimal multicollinearity among predictors (Hair et al. 2011).

Reliability and validity checks. Our model's reliability was confirmed through several metrics (Table 5). Factor loadings surpassed the 0.70 threshold, confirming that indicators properly represented their constructs (Hair et al. 2014). The Average Variance Extracted (AVE) values exceeded 0.50, ensuring a significant proportion of the variance was captured by the constructs. Composite Reliability (CR) scores met the required standards, affirming the model's internal consistency (Tentama and Anindita 2020). To streamline the model and enhance content validity, indicators with loadings below 0.60 were removed, and constructs with low CR and Cronbach's α scores were excluded, ensuring the retention of only robust factors. This approach solidified the foundation for credible and reliable outcomes in our study.

Convergent validity and discriminant validity. Our analysis confirmed convergent validity through high factor loadings and Average Variance Extracted (AVE) values for all constructs. All factor loadings exceeded 0.5, and AVE values surpassed the 0.50 benchmark, indicating that variables closely associated with their respective constructs contribute significantly to the construct's variance (Fornell and Larcker 1981).

Cross loading scores were applied to test the discriminant validity of the existing model. From Table 6, it can be revealed that the factor loadings of each construct are larger than their cross loadings, indicating good discriminant validity of all the included constructs (Hair et al. 2014; Roubertoux et al. 2020).

The correlation coefficient matrix between the variables is shown in Table 7 below. The square root of the AVE of each variable is on the diagonal and is presented in bold. The square

Table 1 Survey questions for UTAUT related constructs.

Performance Expectancy (PE)		
PE1: Usefulness	Sharing tools are useful when I share this type of knowledge. Sharing tools are useful when I get this type of knowledge.	(Chang et al. 2013; Onaolapo and Oyewole 2018; Chatterjee et al. 2020; Lee et al. 2021)
PE2: Effectiveness	I can effectively share this type of knowledge using the sharing tools. I can effectively get this type of knowledge using the sharing tools.	
PE3: Perceived Speed	Using the sharing tools makes me share this type of knowledge more quickly. Using the sharing tools makes me get this type of knowledge more quickly. (Optional) If you do not find it effective or useful to share or get this type of knowledge with sharing tools, can you specify why? How do you want to improve it?	
PE4: Relative Advantage	Sharing tools give me relative advantage when I share this type of knowledge. Sharing tools give me relative advantage when I get this type of knowledge.	(Onaolapo and Oyewole 2018)
Effort Expectancy (EE)		
EE1: Ease of Use	It is easy to use the sharing tools to share this type of knowledge. It is easy to use the sharing tools to get this type of knowledge.	(Onaolapo and Oyewole 2018; Chatterjee et al. 2020; Rumangkit et al. 2023)
EE2: Ease of Access	I can easily access sharing tools whenever and wherever I want to share or get this type of knowledge.	
EE3: Ease of Learning	Learning to operate the sharing tools is easy for me.	(Chang et al. 2013)
EE4: Technical Barrier	It requires much technical expertise to effectively use sharing tools. (Optional) If you feel it is not easy to share or get this type of knowledge, can you specify why? How do you want to improve it?	(Onaolapo and Oyewole 2018)
Social Influence (SI)		
SI1: Platforms' Stance	The platform (MTurk, Prolific, Appen, etc.) believes that I should share this type of knowledge with other crowdworkers. (Optional) In your opinion why do they believe so?	(Bock et al. 2005; Ma et al. 2018; Kim et al. 2020)
SI2: Personal View of Platforms' Stance	I accept and carry out the platform's stance for sharing this type of knowledge even though it is different from mine.	
SI3: Peer Stance	Other crowdworkers believe I should share this type of knowledge with them. (Optional) In your opinion why do they believe so?	
SI4: Personal View of Peer Stance	I respect and put in practice my colleague's stance for sharing this type of knowledge.	
Facilitating Conditions (FC)		
FC1: Technology Integration	The sharing tools integrate well with other technologies I use during crowdwork, such as HIT managers, HIT catchers or visual enhancers. (Optional) If they do not integrate well, can you explain the issues further?	(Ajzen 2020)
FC2: Community and Technical Support	The sharing tools are well supported by the communities or developers, such as providing guidance and maintenance.	(Hicks 2020)
FC3: Compatibility	The sharing tools fit with my work processes and routines, they also support my work activities and goals	(Kamarozaman and Razak 2021)
FC4: Personal Perception	Given the resources, opportunities, and knowledge it takes to use such technologies, it is easy for me to use the forums, channels and plugins for sharing knowledge.	(Vanneste et al. 2013; Lee et al. 2021)
Reciprocity (REC)		
REC1: Others' Willingness	I believe other crowdworkers actively share this type of knowledge.	(Su et al. 2021; Nguyen et al. 2022)
REC2: Personal Willingness	I want to share tasks tips and insights with others because they will do the same in return.	
REC3: Attitude Towards Mutual Help	It is fair to help each other in forums, channels and platforms.	(Maximiano 2017)
Reputation (REP)		
REP1: Image	Sharing this type of knowledge improves my image within the community.	(Zhang et al. 2017; Van Den Besselaar et al., (2019))
REP2: Personal Perception	To what extent do you think sharing knowledge could improve your reputation?	
REP3: Respect	When I share this type of knowledge, the people I work with respect me.	
REP4: Recognition	Sharing this type of knowledge improves others recognition of me.	
REP5: General	Have you thought about sharing knowledge due to concerns about how it might affect your reputation?	
Reward (REW)		
REW1: Benefit	I feel that sharing this type of knowledge will benefit me directly.	

Table 1 (continued)

Performance Expectancy (PE)		
		(Sedighi et al. 2018; Shibayama and Lawson 2021)
REW2: Satisfaction	I feel that sharing this type of knowledge will give me satisfaction.	(Fang and Zhang 2019; Lin et al. 2020; Mahajan and Sharma 2021)
REW3: Enjoyment	I feel that sharing this type of knowledge will give me enjoyment.	
REW4: Knowledge	I feel that sharing this type of knowledge will give me valuable information through interaction with peers.	
Social Interaction Ties (SIT)		
SIT1: Importance of maintaining relationship	It is important to maintain close social relationships with other crowdworkers via the sharing tools.	(García-Sánchez et al. 2019; Kang et al. 2019; Matošková 2020)
SIT2: Support from others	To what extent do your friends or colleagues support or encourage you to use this technology?	
SIT3: Communication frequency	I have frequent communication with other crowdworkers.	
Trust (T)		
T1: Trust via Forums	I trust others when sharing this type of knowledge on forums such as MTurk Crowd.	(LaPlante and Silberman 2016; Ng 2020; Kmieciak 2021)
T2: Trust via Plugins	I trust others when sharing this type of knowledge on plugins such as TurkerView.	
T3: Trust via Social Apps	I trust others when sharing this type of knowledge on social apps such as Slack, Facebook or Telegram.	
T4: Trust of knowledge being valued	I believe other crowdworkers will value my shared knowledge.	
T5: Trust of knowledge being not misuse	When sharing this type of knowledge with peers, I believe others will not abuse my knowledge or claim it as their own ideas.	
Knowledge Sharing Intention (KSI)		
KSI1: Current Intention	I am willing to share this type of knowledge with other crowdworkers.	(Yu et al. 2021)
KSI2: Future Intention	To what extent do you plan to share this type of knowledge via the sharing tools in the future?	
KSI3: Importance of KS	From 1 (very unimportant) to 5 (very important), how important is it to you to share this type of knowledge via sharing tools?	
KSI4: Current Intention	How likely are you to share your skill-based knowledge with other members via forums / channels / plugins?	
Knowledge Sharing Behaviour (KSB)		
KSB1: Behaviour Frequency	On average, how often do you post/share knowledge in forums, channels, or platforms about crowdwork?	(Islam and Afroze 2020; Yu et al. 2021; Mustika et al. 2022)
KSB2: Behaviour upon questions	When I see questions in the sharing tools (such as forums and social apps) that I can answer, I usually share my knowledge with them.	
KSB3: Behaviour after learning	When I have gained a piece of knowledge worth sharing, I share it immediately via the sharing tools.	
KSB4: General	I share skill-based knowledge regularly with peers.	

Table 2 Sample demographics description.

Gender	Count	Percentage	Monthly Income	Count	Percentage
Female	182	40.1%	No more than $100	89	23.4%
Male	261	57.5%	$101 - $300	162	42.6%
Prefer not to say	11	2.4%	$301 - $500	52	13.7%
Age			$501 - $1000	36	9.5%
18–24	24	5.3%	$1001–$5000	28	7.4%
25–34	251	55.4%	More than $5000	13	3.4%
35–44	90	19.9%	**HIT Approval Rate**		
45–54	54	11.9%	Less than 90%	33	7.3%
>55	34	7.5%	90–95%	19	4.2%
Education			95–97.5%	70	15.4%
High School and below	26	5.7%	97.5–100%	332	73.1%
Bachelor	297	65.6%			
Master or Above	130	28.7%			

root of the AVE for all latent variables is more significant than their correlation coefficients with other variables, as shown in Table 7, indicating that the model has good discriminant validity (Fornell and Larcker 1981).

In summary, the measurement model containing PE, EE, FC, REW, KSI, KSB exhibits internal consistency, factor reliability, convergent validity, and discriminant validity. Next, we analysed the structural model to test the path relationships between the

Table 3 Skewness and kurtosis for each observed variable.

Factor	Skewness Statistic	Kurtosis Statistic	Factor	Skewness Statistic	Kurtosis Statistic	Factor	Skewness Statistic	Kurtosis Statistic
PE1	−0.805	2.725	FC3	−0.312	−0.146	SIT2	−0.463	−0.262
PE2	−0.469	0.263	FC4	0.021	2.092	SIT3	−0.649	0.545
PE3	−0.437	−0.345	REC1	−0.434	0.188	T1	−0.587	1.173
PE4	−0.254	0.113	REC2	−0.453	−0.484	T2	−0.585	−0.238
EE1	−0.278	−0.414	REC3	−0.313	−0.328	T3	−0.593	0.969
EE2	−0.345	−0.335	REP1	−0.484	0.161	T4	−0.190	−0.577
EE3	−0.347	−0.321	REP2	−0.422	−0.254	T5	−0.703	1.406
EE4	0.060	0.601	REP3	−0.441	−0.050	KSI1	−0.647	0.767
SI1	−0.649	2.655	REP4	−0.228	0.876	KSI2	−0.450	−0.414
SI2	−0.354	−0.890	REW1	−0.473	−0.106	KSI3	−0.969	1.424
SI3	−0.604	1.231	REW2	−0.521	0.269	KSI4	−0.840	0.377
SI4	−0.355	−0.182	REW3	−0.545	0.014	KSB1	0.015	−0.892
FC1	−0.398	0.462	REW4	−0.200	0.086	KSB2	−0.852	2.252
FC2	−0.432	−0.375	SIT1	−0.556	0.586	KSB3	−0.712	0.408
						KSB4	−0.462	0.881

Table 4 VIF score for each observed variable.

Observed Variable	VIF	Observed Variable	VIF	Observed Variable	VIF	Observed Variable	VIF
EE1	1.655	KSI1	1.143	REP1	1.279	SIT1	1.136
EE2	1.407	KSI2	1.027	REP2	1.066	SIT2	1.037
EE3	1.265	KSI3	1.139	REP3	4.709	SIT3	1.122
EE4	2.367	PE1	1.543	REP4	4.612	T1	1.282
FC1	1.562	PE2	1.407	REW1	1.536	T2	1.202
FC2	1.149	PE3	1.318	REW2	2.871	T3	1.165
FC3	1.526	PE4	1.400	REW3	1.784	T4	1.214
FC4	2.109	REC1	1.088	REW4	4.554	T5	1.320
KSB1	1.080	REC2	1.009	SI1	1.267		
KSB2	1.098	REC3	1.096	SI2	1.073		
KSB3	1.154			SI3	1.179		
				SI4	1.147		

Table 5 Measurement model confidence and validity analysis.

Construct	Measurement Factor	Factor Loading	Cronbach α	CR	AVE
Performance Expectancy (PE)	PE1	0.799	0.742	0.751	0.563
	PE2	0.709			
	PE3	0.720			
	PE4	0.771			
Effort Expectancy (EE)	EE1	0.796	0.726	0.767	0.651
	EE2	0.697			
	EE4	0.913			
Facilitating Conditions (FC)	FC1	0.807	0.764	0.794	0.679
	FC3	0.766			
	FC4	0.893			
Reward (REW)	REW1	0.744	0.698	0.727	0.624
	REW2	0.742			
	REW3	0.876			
Knowledge-sharing Intention (KSI)	KSI1	0.868	0.719	0.763	0.647
	KSI3	0.634			
	KSI4	0.887			
Knowledge-sharing Behaviour (KSB)	KSB2	0.786	0.754	0.766	0.673
	KSB3	0.757			
	KSB4	0.911			

constructs. Figure 2 shows the conceptual framework after the measurement model test.

Control variable analysis. Control variables were measured to account for potential confounding effects on knowledge-sharing intention (KSI) and knowledge-sharing behaviour (KSB). To validate the relevance of these variables, preliminary correlation analyses were conducted between the demographic variables and the endogenous constructs (KSI/KSB). While age showed a statistically significant but weak positive correlation with KSI

Table 6 Cross loading matrix for observed variables.

	PE	EE	FC	REW	KSI	KSB
PE1	0.799	0.534	0.553	0.379	0.480	0.301
PE2	0.709	0.507	0.451	0.415	0.353	0.323
PE3	0.720	0.467	0.382	0.399	0.437	0.355
PE4	0.771	0.535	0.517	0.444	0.491	0.474
EE1	0.544	0.796	0.501	0.416	0.420	0.385
EE2	0.451	0.697	0.448	0.334	0.356	0.277
EE4	0.634	0.913	0.611	0.575	0.520	0.505
FC1	0.549	0.509	0.807	0.374	0.446	0.382
FC3	0.440	0.484	0.766	0.384	0.416	0.325
FC4	0.574	0.604	0.893	0.526	0.517	0.469
REW1	0.405	0.444	0.399	0.744	0.418	0.313
REW3	0.381	0.348	0.375	0.742	0.395	0.377
REW4	0.493	0.520	0.468	0.876	0.543	0.411
KSI1	0.573	0.501	0.539	0.483	0.868	0.431
KSI3	0.337	0.326	0.322	0.379	0.634	0.350
KSI4	0.498	0.465	0.472	0.523	0.887	0.570
KSB2	0.461	0.413	0.466	0.433	0.470	0.786
KSB3	0.330	0.354	0.262	0.335	0.445	0.757
KSB4	0.398	0.442	0.438	0.370	0.485	0.911

Table 7 Correlation coefficient matrix and AVE square root values.

	EE	FC	KSB	KSI	PE	REW
EE	**0.807**					
FC	0.651	**0.824**				
KSB	0.494	0.483	**0.821**			
KSI	0.542	0.561	0.569	**0.804**		
PE	0.680	0.637	0.488	0.593	**0.751**	
REW	0.561	0.527	0.465	0.579	0.544	**0.790**

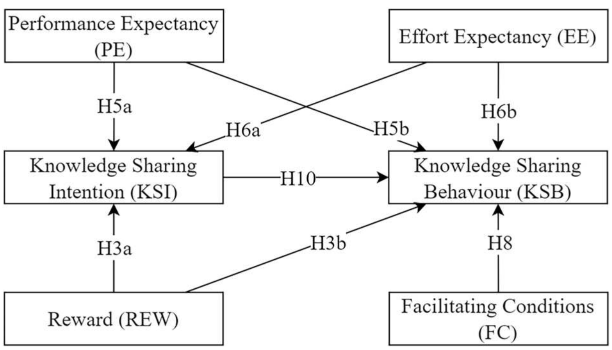

Fig. 2 Modified conceptual framework. The revised conceptual framework presented after evaluating the measurement model. It retains only those constructs and hypothesised paths that were supported by the data, forming the basis for structural model analysis.

(r = 0.19, $p < 0.01$), all other variables (gender, education, income) exhibited no significant associations (all $p > 0.05$).

Given the minimal explanatory power of these demographic variables, and in line with Angosto et al.'s (2023) findings that psychological and situational factors are stronger predictors of behaviour in technology-mediated environments, these control variables were excluded from the final structural equation model to ensure parsimony and focus on the primary research constructs.

Further, while Multi-Group Analysis (MGA) is a valuable tool in PLs-SEM for exploring group-level differences, the distribution of control variables in our dataset posed significant challenges. For example, age and education levels showed highly skewed distributions, with the majority of participants concentrated in a few categories, leaving other groups with insufficient representation (Table 2). This imbalance makes MGA results statistically unreliable and potentially non-representative. Hence, MGA was not conducted to maintain the methodological robustness of the study.

Structural model testing and results. We used PLS-SEM for hypothesis testing based on Principal Component Analysis and Ordinary Least Squares. We specifically chose this method over the more common covariance-based SEM (CB-SEM), because it is prediction oriented, it is more suitable for studies with more complex models and with smaller samples, while it is more robust against distributional assumptions when data is not normally distributed (Sarstedt et al. 2014).

The results of the analysis of all valid paths are shown in Table 8 and Fig. 3. Out of the total 8 research hypotheses, 5 were supported, and 3 were not supported. We were not able to test the remaining hypotheses as a result of the measurement model evaluation.

Specifically, REW (0.323, $p < 0.001$) and PE (0.316, $p < 0.001$) both very significantly affected knowledge-sharing intention (KSI) and both had high effects. In addition, EE also significantly influenced KSI (0.147, $p < 0.01$). However, the influence was not as effective as the first two exogenous constructs REW and PE. In contrast, among the constructs directly influencing final behaviour, KSI had a significant effect on KSB (0.331, $p < 0.001$) and had the largest effect. Notably, EE had a relatively significant effect on KSB (0.138, $p < 0.05$). Ultimately, unlike the assumption of the traditional UTAUT model, the hypothesis of the effect of Facilitating Conditions (FC) on KSB was not supported in this study.

Explanatory and predictive power. The structural model's efficacy was assessed using the coefficient of determination (R^2) and predictive relevance (Q^2). The R^2 values for knowledge-sharing intention (KSI) and behaviour (KSB) were 0.454 and 0.393, respectively, indicating moderate explanatory power for these constructs (Table 9). Predictive relevance, assessed through Q^2, demonstrated positive values for both KSI and KSB, confirming the model's capability to predict endogenous constructs effectively (Hair et al. 2013). Furthermore, specific exogenous constructs such as reward mechanisms and performance expectancy showed medium predictive relevance ($q^2 > 0.15$) to both KSI and KSB, underscoring a satisfactory predictive performance of the model.

Overall fitness of structural model. The model's overall fit was evaluated using multiple indices. As shown in Table 10, the Standardised Root Mean Square Residual (SRMR) was 0.072, suggesting a good fit with observed data (Hu and Bentler 1999). Although the Root Mean Square Residual Covariance (RMS-theta) was slightly above the optimal threshold at 0.176, it remained within acceptable limits (Bentler and Bonett 1980). The composite Goodness of Fit (GoF) value of 0.373 exceeded the threshold of 0.36, affirming a high overall fitness of the structural model according to PLS-SEM standards (Tenenhaus et al. 2004).

Indirect Effects Test. We used bootstrapping to examine the mediating effect within this structural model. The estimates of indirect effects and 95% confidence intervals were derived from 5000 Bootstrap samples. From the indirect relationships, it can be seen from Table 11 that PE significantly affects KSB indirectly through KSI (t value = 4.462, $p < 0.001$), EE significantly affects

Table 8 Structural equation model path coefficients.

Hypothesis	Path Relation	Relationship	Path Coefficient (t-value)	Supported or Not
H3a	REW - > KSI	positive	0.323 (6.545) ***	Supported
H5a	PE - > KSI	positive	0.316 (5.835) ***	Supported
H6a	EE - > KSI	positive	0.147 (2.871) **	Supported
H3b	REW - > KSB	positive	0.099 (1.605)	Not Supported
H5b	PE - > KSB	positive	0.084 (1.374)	Not Supported
H6b	EE - > KSB	positive	0.138 (2.182) *	Supported
H8	FC - > KSB	positive	0.101 (1.645)	Not Supported
H10	KSI - > KSB	positive	0.331 (5.191) ***	Supported

***$p < 0.001$ indicates very strong evidence against the null hypothesis. **$p < 0.01$ shows strong evidence against the null hypothesis. *p between 0.01 and 0.05 indicates good evidence against the null hypothesis.

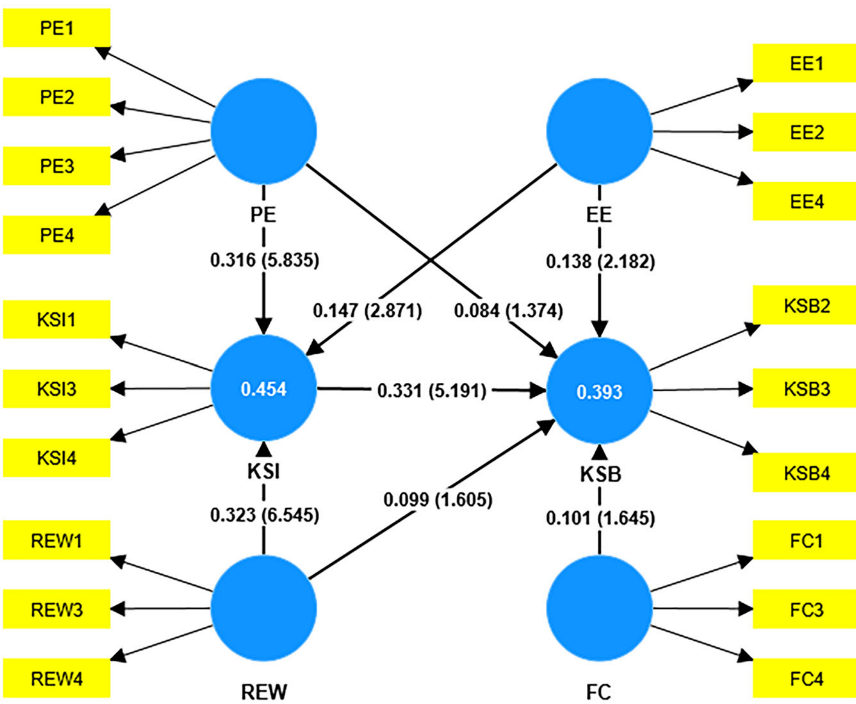

Fig. 3 Structural model with path coefficients and t-values. The final PLS-SEM structural model showing path coefficients and associated t-values between constructs on each arrow. Note that both statistically significant and non-significant paths are visualised in the figure, and bold arrows do not exclusively indicate significance.

Table 9 Path coefficient with explanatory power test and predictive ability test scores.

Hypothesis	Path Relation	Path Coefficient (t-value)	Supported or Not	R^2	q^2	95%CI Lower	95%CI Upper	Q^2
H3a	REW - > KSI	0.323 (6.545) ***	Supported	0.454	0.161	0.227	0.419	0.441
H5a	PE - > KSI	0.316 (5.835) ***	Supported		0.108	0.202	0.416	
H6a	EE - > KSI	0.147 (2.871) **	Supported		0.038	0.045	0.246	
H3b	REW - > KSB	0.099 (1.605)	Not Supported	0.393	0.165	−0.018	0.219	0.314
H5b	PE - > KSB	0.084 (1.374)	Not Supported		0.152	−0.043	0.201	
H6b	EE - > KSB	0.138 (2.182) *	Supported		0.140	0.006	0.254	
H8	FC - > KSB	0.101 (1.645)	Not Supported		0.160	−0.016	0.224	
H10	KSI - > KSB	0.331 (5.191) ***	Supported		0.117	0.208	0.455	

***$p < 0.001$ indicates very strong evidence against the null hypothesis. **$p < 0.01$ shows strong evidence against the null hypothesis. *p between 0.01 and 0.05 indicates good evidence against the null hypothesis.

KSB indirectly through KSI (t value = 2.821, $0.001 < p < 0.01$), and EE significantly affects KSB indirectly through KSI (t value = 3.787, $p < 0.001$). In addition, it is revealed that EE has a relatively significant direct effect on KSB (t value = 2.182, $0.01 < p < 0.05$), and this effect (path coefficient = 0.138, $p < 0.01$) is greater than the indirect effect on KSB through KSI (path coefficient = 0.049, $p < 0.001$). Combined with the previous path analysis table, it can be found that the construct that causes the largest total effect on KSB is KSI (path coefficient = 0.331, $p < 0.001$), followed by Reward (total effect = 0.206).

Discussion

This study employed a Partial Least Squares Structural Equation Modelling (PLS-SEM) approach to investigate the determinants of skill-based knowledge-sharing among crowdworkers. The model included four exogenous variables (Performance Expectancy, Effort Expectancy, Reward, Facilitating Conditions) and two endogenous variables (Knowledge-sharing Intention, Knowledge-sharing Behaviour). Below, we first provide an overview of the key findings, followed by a detailed discussion on theoretical and practical implications.

Interpretation and overview of findings. Based on our results, Reward significantly influenced Knowledge-sharing Intention (path coefficient = 0.323, $p < 0.001$), underscoring that intrinsic motivations such as satisfaction and enjoyment are critical drivers of knowledge-sharing. The analysis also revealed a significant indirect effect of Reward on Knowledge-sharing Behaviour, suggesting that non-material rewards, like peer learning during communication, play a substantial role.

Effort Expectancy also showed a significant positive correlation with Knowledge-sharing Intention (path coefficient = 0.147, $p < 0.01$), indicating that easier access and usability of knowledge-sharing tools enhance the willingness to share. In addition, in the test of indirect effect, EE was found to have both direct effect (0.138) and indirect effect (0.049) on behaviour (KSB). The identification of Effort Expectancy's direct effect on Knowledge-sharing Behaviour extends the UTAUT framework within the knowledge-sharing domain, suggesting that the usability of communication tools directly affects the generation of final sharing behaviours, beyond merely affecting users' intentions.

Performance Expectancy significantly affected Knowledge-sharing Intention (path coefficient = 0.316, $p < 0.001$), reflecting that the effectiveness and speed of the knowledge-sharing tools significantly influence sharing willingness.

Comparing the total effects, REW (0.206) exerted a slightly higher overall influence on Knowledge-sharing Behaviour than PE (0.189), and EE (0.187). This implies that participants perceive enjoyment, satisfaction, and knowledge from others during communication as more influential on their final sharing behaviour than whether the sharing technique is efficient and effective. Furthermore, KSI had the highest total effect (path coefficient = 0.331, $p < 0.001$) on KSB, confirming the consensus established by prior studies utilising the UTAUT framework (Attuquayefio and Addo 2014; Yee and Abdullah 2021). Notably, in conjunction with the structural model's study of indirect effects, it can be found that PE, EE and REW all further influence the final behaviour via KSI.

Table 10 Metrics to test model fit.

SRMR (< 0.08)	GoF (> 0.36)	RMS-theta (< 0.12)
0.072	0.373	0.176

Theoretical implications. Overall, our findings indicate that enjoyment, satisfaction, and efficient information exchange are crucial in promoting knowledge-sharing. Additionally, the performance expectancy and ease of use of communication tools significantly impact sharing behaviours, aligning with the workers' need for tools that integrate seamlessly into their work strategies.

Performance and effort expectancy are confirmed as key motivators, highlighting the importance of tool usability and perceived benefits in fostering knowledge-sharing behaviours (Gagné et al. 2019; Nguyen 2021). This does not come as a surprise as numerous technology acceptance studies, including meta-analyses, have confirmed their explanatory power (Angosto et al. 2023; Wei et al. 2024). In line with this, we show that technology acceptance plays a crucial role in facilitating knowledge-sharing, and unlike broader studies on technology acceptance within organisations, we specifically explored knowledge sharing behaviour among crowdworkers, revealing unique adoption patterns in the crowdsourcing environment. Workers' perceptions of the utility and benefits of knowledge-sharing tools—termed performance expectancy—greatly enhance their willingness to share (Zhao et al. 2018; Lee et al. 2021). Effort expectancy, or ease of use, also significantly boosts knowledge-sharing (Nguyen and Malik 2022b). Intuitive and user-friendly tools are linked to increased sharing activities, resonating with studies in different contexts like mobile payments and organizational technology use (Hung et al. 2019; Nguyen 2021). This confirms the critical importance of usability in enhancing both Knowledge-sharing Intention (KSI) and Knowledge-sharing Behaviour (KSB), reinforcing the relevance of the technology acceptance model across diverse user groups.

Our findings further highlight that intrinsic motivations such as altruism and personal satisfaction significantly influence knowledge-sharing among crowdworkers. We consider this to be an important finding. As earlier noted by Wang et al (2022b), earlier studies on knowledge sharing behaviours among virtual communities provide contradictory and inconclusive results in terms of the role of intrinsic rewards and motivations. We show that workers who derive fulfilment from aiding others are more likely to share knowledge, with enjoyment and satisfaction acting as powerful intrinsic motivators (LaPlante and Silberman 2016; Osterbrink and Alpar 2021), and further extend this to showcase the universal role of intrinsic rewards within the professional virtual community of crowdworkers.

Interestingly, Facilitating Conditions did not significantly influence knowledge-sharing behaviour in our analysis. To date, studies on technology acceptance and use have offered conflicting results in terms of the impact of this factor on user behaviour. For example, Wei et al. (2024) showcase that this factor does not have any influence on the use of robotaxis, while Alagood et al. (2024)

Table 11 Illustration of indirect effects.

Independent Variable	Intervening Variable	Dependent Variable	Direct Effect (t-value)	Indirect Effect (t-value)	Total Effect (t-value)
PE	KSI	KSB	0.084 (1.374)	0.105 (4.462) ***	0.189 (3.096) **
EE			0.138 (2.182) *	0.049 (2.821) **	0.187 (2.953) **
REW			0.099 (1.605)	0.107 (3.787) ***	0.206 (3.056) **

***$p < 0.001$ indicates very strong evidence against the null hypothesis. **$p < 0.01$ shows strong evidence against the null hypothesis. *p between 0.01 and 0.05 indicates good evidence against the null hypothesis.

found the reverse, and specifically that facilitating conditions have a significant influence over the adoption of relational technology. For our study, we posit that the influence of facilitating conditions is possibly captured by other factors. As facilitating conditions essentially reflect perceptions with regards to whether support is needed for performing a particular behaviour, and whether something is easy and convenient to do, we would like to echo Jabeen et al. (2023) in that, possibly, the influence of this factor is captured by effort expectancy.

Practical implications. Understanding crowdworkers' adoption of KS tools guides effective design principles. Our findings indicate that enhancing the usability and accessibility of these platforms—through cross-platform compatibility and integration of knowledge-sharing features into microtask environments—is crucial. Additionally, incorporating elements that boost enjoyment, and satisfaction can significantly motivate crowdworkers to engage with these tools.

A notable practical challenge is that knowledge in community forums and apps typically remains unstructured and scattered, hindering systematic retrieval and use. Large Language Model powered tools, such as browser extensions and knowledge management systems, are key to organising information and making it more accessible and useful for crowdworkers. Such tools have the potential to enhance knowledge-sharing behaviours among crowdworkers by reducing technical barriers and improving access to high-quality information (Olan et al. 2024; Christoforou et al. 2024).

Furthermore, tools should be intentionally designed to encourage active community participation, ensuring contributions are effortless to provide and acknowledged within the community. This could involve mechanisms such as progress bars or enhanced interaction features, which have been effective in other interactive online environments. Additionally, incorporating gamification elements could further support active and ongoing involvement (Ernestivita et al. 2024).

Finally, our research advocates developing an integrated knowledge management system serving as a centralized solution for crowdworkers to access, share, and retrieve skill-related information. Such a system would consolidate dispersed information, streamline the access process, and facilitate ongoing information updates and sharing. In doing so, they enhance the overall effectiveness, usability, and sustainability of knowledge-sharing platforms.

Conclusion

In this study, we set out to explore the primary motivation for knowledge sharing behaviour among crowdworkers and the impact of technology-related and social interaction factors. Our findings indicate that the satisfaction derived from helping others, a form of reward, significantly impacts positively knowledge sharing behaviour, and is thus the major motivation for engaging in this type of behaviour. This finding also highlights the importance of support and altruism within this community. In addition, we identified performance and effort expectancy as pivotal technology-related determinants shaping one's intention to share knowledge with their community.

The results emphasize the importance of designing effective communication tools to facilitate knowledge-sharing activities among crowdworkers. Tool developers are therefore encouraged to enhance usability, interactivity, and overall functionality. Our findings also advocate for strategically designed rewards to motivate knowledge-sharing, highlighting the importance of recognition and professional reputation. Such enhancements are crucial not only for facilitating effective knowledge flow but also for strengthening the sense of community among crowdworkers, ultimately promoting the sustainable development of the crowdsourcing industry.

Despite its contributions, our study has several limitations. First, data collection relied on self-reported questionnaires, potentially introducing biases and limiting accuracy. Furthermore, the sample was limited to English-speaking crowdworkers available during data collection, which may not represent the global crowdworker population. The above can be possibly addressed in the future through cross-country coordinated projects by sampling crowdworkers of different ethnicities and nationalities over a longer period, which can lead to a more diverse linguistic and cultural cohort.

Additionally, our study does not fully capture the impact of recent advancements in AI-based tools. Recent advancements in AI-based tools have significantly reshaped knowledge-sharing and collaborative behaviours across diverse domains, including education, enterprise systems, and crowdsourcing. Large language models (LLMs) such as ChatGPT streamline real-time, structured interactions, reducing the cognitive and temporal barriers to sharing knowledge (Nguyen and Malik 2022a; Kernan Freire et al. 2024). Specifically within crowdsourcing, AI-powered tools enhance knowledge exchange by improving efficiency, engagement, and the quality of information (Zhang 2022; Ulmanen et al. 2024; Christoforou et al. 2024). These advancements underscore the potential of AI in facilitating more accessible, efficient, and collaborative knowledge-sharing practices. Future research should explore how these tools, including LLM-powered chatbots and automated knowledge systems, influence knowledge-sharing intentions and behaviours, therefore providing valuable insights into optimising crowdsourcing platforms for the AI future.

Another limitation is the uneven distribution of control variables such as age and education across participant groups. While these variables were analysed for their correlations with endogenous constructs, the imbalance in group sizes limited the feasibility of conducting Multi-Group Analysis (MGA). Future studies could benefit from more balanced sampling to explore group-level differences more comprehensively. We also propose that adopting a mixed methods approach could be beneficial, too, whereby selected crowdworkers could be interviewed to gain deeper insights. Additionally, the rise of text generation tools like ChatGPT raises concerns about response authenticity, highlighting the need for mechanisms to verify originality in future studies. Methodological issues, such as inadequate reliability and validity for factors like social influence and trust, prevented their inclusion in our structural model.

An important consideration is the aspect of task complexity. In our study, we specifically focused on crowdworkers working in MTurk, where they engage with microtasks. Microtasks are self-contain and small tasks that typically do not require a particular skillset (Deng and Joshi 2016) (e.g., questionnaire completion, image annotation). However, crowdworkers may engage with larger tasks whose complexity is higher and thus require specific skills and provide better returns. As such, we consider that further research can focus on macro-tasks, too, and examine whether our findings are still relevant.

Lastly, the design, development, and testing of targeted reward mechanisms to incentivise knowledge sharing represents another promising direction. Although beyond the scope of our current study, future research could provide valuable insights by evaluating how specific reward structures influence knowledge-sharing behaviours and by critically examining both benefits and potential drawbacks associated with AI-enabled tools designed for this purpose.

Data availability

The datasets analysed in this study are available in the OSF repository: https://osf.io/rjw5q/?view_only=756d839ccef846ea84dea98b501ea8c5.

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Note

1 A forum section showcasing Turker of the Month: http://mturkforum.com/index.php?forums/turker-of-the-month.47/.

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Author contributions

HX is the lead author of this manuscript. EZ, SD, and AC jointly supervised this work. They provided guidance and oversight at different stages, including the development of the theoretical framework, technical implementation, experimental procedures, and final manuscript preparation. All authors contributed to and reviewed the manuscript.

Competing interests

The authors declare no competing interests.

Ethical approval

This study received ethical approval from the University of Sheffield's Information School Ethics Review Committee (Reference Number: 049528). Approval was granted on 08/11/2022, following the review of the submitted research ethics application (Form submission date: 04/11/2022), participant information sheet (26/10/2022), and participant consent form (29/09/2022). The research was conducted in accordance with the University's Research Ethics Policy and Good Research & Innovation Practices Policy. All personal data collected during the project adhered to relevant legal and regulatory guidelines. All procedures performed in this study involving human participants were in accordance with the ethical standards of the institutional research committee and with the 1964 Helsinki Declaration and its later amendments or comparable ethical standards.

Informed consent

Participation in this study was entirely voluntary and posed no known physical, emotional, or psychological risks. Electronic informed consent was obtained from all participants between August 3 and August 27, 2023, after providing them with a clear explanation of the research purpose, procedures, participant tasks, data confidentiality, and their right to withdraw at any time without penalty. All participants explicitly confirmed their consent before beginning the questionnaire.

Additional information

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