Trust dimensions and operational performance in VR-based drone tasks in construction

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Abstract

Purpose – The successful deployment of drones in construction increasingly depends on human operators' willingness to work collaboratively with robotic systems. However, limited understanding of how trust develops during human–drone interaction and its relationship to performance outcomes hampers the design of effective human–drone interaction frameworks and adoption strategies.

Design/methodology/approach – We conducted a within-subjects experiment with 41 participants who completed collaborative drone flight operations in a virtual reality environment. Trust was measured pre- and post-interaction across four dimensions: perceived risk, benevolence, competence and reciprocity. Objective performance was quantified via task completion time and collision count.

Findings – One-sample *t*-tests revealed significant increases in trust for benevolence (d = 0.35), competence (d = 0.44) and reciprocity (d = 0.43), with overall trust improving substantially (d = 0.48, $p = 0.004$). Larger increases in trust were associated with operational performance, inversely correlating with both completion time ($r = -0.60$, $p < 0.001$) and collisions ($r = -0.71$, $p < 0.001$). Among trust dimensions, perceived reciprocity was the most associated with objective performance in this task, showing significant correlations with reduced collisions ($r = -0.32$, $p = 0.041$).

Originality/value – Collaborative interaction fosters measurable trust gains in humans toward drones, with reciprocity, the perceived sense of mutual responsiveness, showing a significant association with performance in the VR-based inspection task. These findings offer preliminary insights that may help inform the design of collaborative drone systems that consider mutual responsiveness, the development of operator training programs focused on reciprocal interaction patterns and organizational strategies to accelerate autonomous technology adoption in construction.

Keywords Trust, Competency, Benevolence, Construction, Human–drone interaction

Paper type Research article

1. Introduction

The adoption of robotic drones in construction has surged in recent years, revolutionizing core processes such as site surveying, progress monitoring, inspection and collaborative assembly tasks (Dukowitz, 2025; Ramirez Rufino *et al.*, 2023). Industry reports now consistently indicate that many large construction firms are deploying unmanned aerial systems (UAS), citing enhanced efficiency, data quality and safety oversight as primary motivators (ABC Hawaii, 2026; Jeelani and Gheisari, 2021; Skydio Blog, 2025; Xing and Johnson, 2023; Zhou and Gheisari, 2018). However, despite their rapid integration, construction sites continue to experience rising accident rates and operational disruptions involving human–drone interactions. This trend has spurred renewed attention not only on technical training for drone operators but also on critical human factors that influence safe and effective collaboration between construction personnel and robotic systems (Daoud *et al.*, 2025).

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Trust is widely recognized as a determinant of appropriate reliance in automation and robotics (Endsley, 2017; Walker *et al.*, 2023). Trust influences whether users accept a system, delegate tasks, calibrate monitoring intensity and decide when to intervene (Chen *et al.*, 2018; Jensen *et al.*, 2020; Okamura and Yamada, 2020). In practice, trust governs an operator's willingness to delegate tasks, respond flexibly to robotic assistance, intervene intelligently during errors and maintain a balanced reliance on automation during routine and abnormal conditions. Insufficient trust can undermine adoption and escalate risk, resulting in either over-reliance on autonomous functions or unnecessary manual intervention that negates productivity gains (Haney and Liang, 2024). Multidimensional perspectives provide a more actionable explanation of trust by identifying distinct drivers of reliance decisions (Pinto *et al.*, 2022). Rather than treating trust as a single scalar, these models decompose trust into components such as perceived competence, perceived benevolence or intent and perceived risks, distinct dimensions of trust in an assisted drone system, rather than as interpersonal attitudes (Gulati *et al.*, 2018; Schoeller *et al.*, 2021). In the context of human–drone interaction, these constructs can be interpreted as distinct dimensions of trust in an assisted drone system, rather than as interpersonal attitudes (Kluge *et al.*, 2026). These dimensions suggest that understanding which aspects of trust change and which matter for performance is more informative than knowing that overall trust is high or low. Therefore, trust is increasingly recognized as central to effective human–robot teaming, with empirical studies examining factors such as transparency, reliability, perceived competence and risk perceptions (Pinto *et al.*, 2022). Soft skills training focusing on attitude and adaptability has also been linked to improved collaboration and safer deployment of robotic technologies. While the role of trust in successful human–robot collaboration is widely endorsed, there is limited systematic understanding of how trust develops during collaborative tasks in construction (Chang and Hasanzadeh, 2024), particularly in relation to drones operating in complex, cluttered and safety-critical environments.

Although several studies have demonstrated associations between trust and human–robot collaboration performance in robotics or remote context, the construction domain, particularly with drones, lacks in-depth empirical assessment of which specific trust dimensions most directly relate to objective task performance outcomes. The few recent attempts to link trust and performance often rely on overall trust scores or focus on physiological prediction mechanisms, without systematically disentangling the unique contributions of different facets of trust (Chang *et al.*, 2025; Guo *et al.*, 2025), specifically when addressing drones in construction. As a result, it remains unclear which trust dimensions are most associated with team performance, reduce errors and foster sustainable technology adoption on construction sites, limiting the evidence available to practitioners and system designers seeking to inform future drone deployment strategies. To address this gap, the present study investigates three core research questions in the context of a human–drone collaborative inspection task conducted in a VR construction environment.

RQ1. How does human trust in robots change from before to after collaborative interaction?

RQ2. To what extent does change in trust correlate with task performance in the collaborative task?

RQ3. Which trust-related dimensions among perceived risk, benevolence, competence and reciprocity are most associated with objective task performance?

By examining trust development across these four dimensions and linking them to objective performance metrics, this study seeks to identify which facets of trust are most associated with safe and efficient construction drone operations in this context, offering preliminary, context-specific evidence to inform future system design, operator training and organizational deployment research.

2. Literature review

Drones are increasingly adopted in construction because they provide rapid, repeatable, and comparatively low-cost access to jobsite information (Ramirez Rufino *et al.*, 2023; Zhou and Gheisari, 2018). Prior studies describe applications such as surveying and mapping, progress monitoring, visual documentation for quality and claims, and safety reconnaissance, where aerial viewpoints can reduce worker exposure and improve situational awareness on active sites (Bae *et al.*, 2022; Fassbender *et al.*, 2018; Zhou and Gheisari, 2018). Use of drones are also shifting from periodic documentation toward more interactive operations (e.g. guided inspection), which places greater emphasis on human decision-making during collaboration rather than on data capture alone (Ajith and Jolly, 2021; Liu *et al.*, 2020). Recent work on VR-based drone and construction training simulators indicates that virtual environments with physics-based flight and construction-specific geometry can provide realistic and effective surrogates for real-world operations (Jeelani and Gheisari, 2021; Zhou and Gheisari, 2018). VR systems such as DroneSim have been shown to support building inspection training with comparable perceived workload and training value to real flight, while enabling repeatable, risk-free practice in construction contexts (Albeaino *et al.*, 2022; Hussain *et al.*, 2026). More broadly, visualization technologies including VR simulations have been found sufficient and acceptable for training complex, high-risk construction tasks and improving operational skills and safety behavior, supporting their use as ecologically valid testbeds for human-technology interaction and safety research (Park *et al.*, 2023; Pedro *et al.*, 2019).

Building on this background on drone use and VR-based training in construction, the following subsection examines how trust shapes human–drone collaboration in these environments. Human–drone interaction (HDI) in construction is uniquely demanding because the work environment is dynamic, cluttered and safety-critical (Albeaino *et al.*, 2021; Jeelani and Gheisari, 2021). Variable lighting, dust, vibration and occlusion can degrade sensing and increase uncertainty in drone behavior; simultaneously, moving equipment, time pressure and proximity to workers and assets elevate the consequences of navigation or control errors (Albeaino *et al.*, 2023; Erat *et al.*, 2018; Ghazali and Rahiman, 2022). Safety-oriented discussions therefore emphasize that successful deployment depends not only on technical capability and compliance, but also on interaction processes that support safe coordination, clear feedback about system state, understandable behaviors and operational procedures that fit within jobsite constraints (Cauchard *et al.*, 2016; Lee and Yu, 2023). Without such alignment, operators may over-monitor, intervene too frequently or hesitate to rely on the drone even when it is capable, reducing potential productivity and safety benefits (Cauchard *et al.*, 2016). Trust-in-automation theory emphasizes that trust is dynamic and experience-dependent: it evolves as users observe system behavior, interpret outcomes and update expectations based on perceived reliability (Endsley, 2017; Okamura and Yamada, 2020; Walker *et al.*, 2023). These principles are directly relevant to drone operations in construction, where performance can vary with environmental conditions and where operator actions can either stabilize or degrade task execution (Jensen *et al.*, 2020).

Trust judgments commonly reflect perceived competence, perceived intent or benevolence and perceived risk (Han and Yan, 2019; Pinto *et al.*, 2022). For drones, these dimensions are salient: competence relates to stable flight, accurate maneuvering and dependable responses; benevolence captures whether the drone's behavior appears to prioritize the operator's goals and safety; and risk reflects perceived likelihood and severity of adverse outcomes (Ramezani *et al.*, 2024; Xing and Johnson, 2023). Multidimensional models typically distinguish competence, benevolence or intent and risk/uncertainty as core components that shape reliance decisions in human–robot interaction (Wu *et al.*, 2024). Reciprocity is relevant in interactive collaboration: operators may trust more when the drone appears to move in concert with their control inputs, through smooth, contingent and predictable responses to their actions and constraints (e.g. adjusting smoothly to inputs, avoiding abrupt or unexpected motion), creating an experience of coordinated responsiveness rather than one-way automation (Nikolaidis *et al.*, 2017; Ramezani *et al.*, 2024; Sandoval *et al.*, 2016). In the present study, reciprocity is interpreted as perceived mutual responsiveness under shared control, consistent with perception-based accounts of reciprocity in Human-robot interaction (HRI), rather than as fully bidirectional adaptive behavior. Together, these dimensions motivate examining not only whether trust increases, but which trust components drive reliance and performance (Pinto *et al.*, 2022).

Despite growing recognition that trust is central to effective human–robot collaboration, several gaps remain. First, limited understanding exists regarding trust development during active collaboration (as opposed to passive observation), particularly for drone operations where co-presence, motion cues and dynamic task demands can meaningfully alter perceived risk and reliance behavior (Hopko and Mehta, 2024; Schoeller *et al.*, 2021). Second, construction-domain evidence is still comparatively limited relative to robotics, remote operation and transportation automation contexts, leaving uncertainty about how trust functions under jobsite conditions characterized by high consequences, and competing attentional demands. Third, although many studies link trust with performance, fewer studies systematically disentangle which trust dimensions uniquely explain performance variance; as a result, design and training recommendations often remain broad rather than mechanism specific. Multidimensional models suggest that competence, benevolence and risk may differentially shape reliance decisions, yet empirical evidence linking these dimensions to objective performance in construction contexts remains sparse, and reciprocity has rarely been examined explicitly. To address these gaps, the present study examines trust development across four dimensions – risk, benevolence, competence and reciprocity – measured before and after a collaborative drone interaction in a construction-relevant task context. The study links these dimensional trust measures to objective performance outcomes and evaluates which trust facets are associated with performance variance. By moving from global trust scores to a dimension-level model connected to performance, this approach offers preliminary, context-specific evidence on which trust-building mechanisms and calibration aspects may warrant further investigation in future system design and training research.

3. Research methodology

This study employed a within-subjects experimental design to investigate trust development and its relationship to objective task performance in human–drone collaboration. Participants completed collaborative drone-assisted site inspection tasks in a virtual reality (VR) environment, with trust assessed before and after the complete interaction sequence. This within-subjects design maximized statistical power by controlling for individual differences and enabling direct assessment of trust change attributable to the collaborative human–drone interaction. Students from architecture, engineering and construction background were recruited from Department of Construction Science. All participants received compensation for their time. This study was approved by institutional review board. Informed consent was obtained from all participants prior to any data collection, and confidentiality was maintained throughout data collection and analysis.

3.1 VR system architecture

The VR environment was developed using the Unity© game engine with C# programming language on a Dell© Precision 5,820 Tower workstation. The system was configured with an Intel© Core™ i9-10900X processor running at 3.70 GHz with 20 logical cores, 128 GB of RAM and an NVIDIA© RTX A4500 graphics card. An HTC© Vive Pro head-mounted display (HMD) was integrated to facilitate immersive VR interaction and real-time performance monitoring. The drone control interface was designed to reflect realistic operational parameters, featuring dual-axis maneuvering (vertical and horizontal movement), camera control and flight stabilization. In practice, this stabilization logic continuously smooths and regulates the drone's motion in response to the operator's joystick inputs and the virtual environment, so that control is shared between operator and system rather than being a simple one-to-one manual mapping of commands to movement. Although autonomy is restricted to low-level stabilization, the continuous bidirectional coupling provides a basis for participants to experience the interaction as reciprocal in the sense of mutual responsiveness, consistent with the HRITS scale. The whole experimental setup and virtual environment with drone interface is illustrated in Figure 1.

The virtual environment rendered a multi-storey construction site populated with obstacles, scaffolding, equipment and materials typical of active jobsites, as well as non-player construction workers, concurrent construction robots and ambient machine noise to enhance ecological validity. Drone motion was controlled via a flight interface supporting dual-axis translation, camera control and stabilization, and collisions were registered when the drone's body intersected modeled objects or agents, so that recorded collision events correspond to navigation errors that would be safety-relevant in an actual site environment rather than arbitrary gaming penalties. After the VR environment was developed, five experts with experience in construction safety and familiarity with VR and robotics (advanced degrees or ≥5 years of safety-related experience) explored the simulation, evaluated the scenario design and provided feedback that was used to refine the realism and usability of the task. The task duration was standardized at approximately 30 minutes, with performance metrics (completion time and collision count) automatically logged in CSV format at millisecond-level precision by the VR system. The immersive and complex environment ensured that trust calibration occurred in an ecologically valid context representative of real-world drone operations in active construction settings. The overall experimental setup and virtual environment, including the drone control interface, are illustrated in Figure 1.

3.2 Task selection and experimental process

Participants were first recruited and scheduled individually for a laboratory session. After arrival, they received an overview of the study and completed an informed consent process, followed by standardized written and verbal instructions (5 minutes). Next, participants filled out the pre-intervention trust questionnaire (5 minutes). Trust was measured using the human–robot interaction trust scale (HRITS), a validated instrument for assessing trust in HRI that adapts a multidimensional human–computer trust model to human–robot contexts (HRTIS, 2023; Pinto *et al.*, 2022). In the HRITS, the reciprocity-related items assess the perception of mutual responsiveness and the quality of interaction between humans and robots. In our joystick-controlled, stabilized drone task, we interpret higher reciprocity scores as a perceived

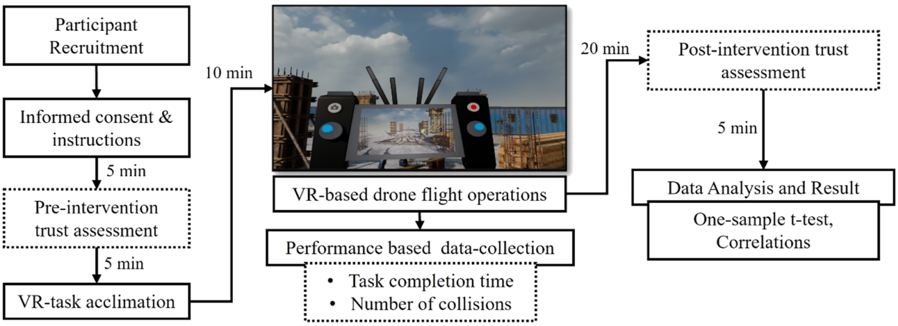

Figure 1. Experimental setup. Source: Authors' own work

sense that the operator and the controller are jointly and contingently shaping the drone's motion under shared control. Participants then completed a brief VR task acclimation phase to become familiar with the headset, controls and basic drone maneuvering. After acclimation, participants performed the VR-based drone flight operations task, during which they navigated the drone within the simulated construction environment to identify potential hazards. However, the aim of this paper is not to assess their hazard identification skill. The task was selected based on its ability to impose realistic cognitive and perceptual demands on operators, elicit continuous interaction with the drone in a safety-relevant construction context and generate objective performance measures – completion time and collision count – that are sensitive to differences in trust and reliance behavior rather than general gaming skill (Behzad Esmaeili, 2017; Hussain *et al.*, 2024). Throughout this phase, performance data were automatically recorded, including task completion time and number of collisions. Immediately after finishing the task, participants completed the post-intervention trust questionnaire (≈5 minutes). Finally, the dataset was analyzed using one-sample *t*-tests on trust change scores and correlation analyses between trust measures and performance indicators. The experimental procedure is illustrated in Figure 2, which outlines the sequential steps from participant recruitment through data analysis, including the timing of trust assessment points and performance data collection during the VR-based drone inspection task.

3.3 Data analysis

All analyses were conducted on data from $N = 41$ participants. The performance data was extracted from the experimental logs and analyzed using IBM© SPSS Statistics Version 28, with count-data models estimated in Python. A priori power analysis in G*Power (two-tailed, $\alpha = 0.05$; $1 - \beta = 0.80$) indicated that a sample size of approximately 29–37 would be sufficient to detect medium effect sizes for the planned *t*-tests and correlations, suggesting that the final sample provided adequate statistical power (Kang, 2021). The dataset comprised change scores for four trust-related dimensions, perceived risk, benevolence, competence and reciprocity, and an overall trust change score (Δ), computed as post minus pre–interaction ratings. Objective operational performance was defined using two VR-logged indicators of task execution quality: task completion time in seconds and number of drone collisions with

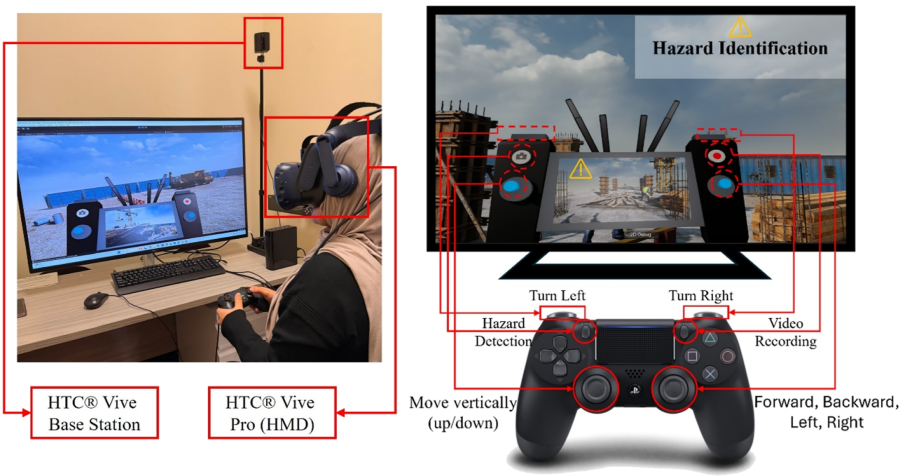

Figure 2. Experimental procedure and timeline for the human–drone collaboration trust study. Source: Authors' own work

environmental objects or agents, which respectively index efficiency and safety-relevant errors during the inspection flight. Descriptive statistics (mean, standard deviation, range) were calculated for all variables. No missing data was present. Completion time approximated a continuous, near-normal distribution and was therefore treated as such throughout. Collision count, however, showed marked positive skew and several extreme values, consistent with its nature as a non-negative, right-skewed count outcome. This distributional profile indicated that treating collisions as a continuous variable, as in ordinary least-squares regression or correlation-only analysis, could violate the assumptions underlying those methods and produce a misleading picture of the trust-performance relationship.

To address RQ2 and RQ3 (associations between trust and performance), bivariate Pearson correlations were computed between (a) overall trust change (Δ) and each performance measure (completion time, collisions), and (b) each trust dimension change score (Δ Risk, Δ Ben, Δ Comp, Δ Recip) and each performance measure. Given the presence of outliers and non-normality, particularly for collisions, Spearman's rank-order correlations (ρ) were also calculated as a robustness check. All tests used a two-tailed significance level of $\alpha = 0.05$. For completion time, these correlation analyses serve as the primary basis for inference, consistent with its continuous, approximately normal distribution. For collision count, Pearson and Spearman correlations are reported for descriptive and robustness purposes only; because collision count is a discrete, non-negative and over-dispersed outcome, formal statistical inference for this variable is instead based on the count-data regression models described below.

Because collision count is a discrete, skewed outcome, generalized linear models for count data were used as the primary analytic approach. A Poisson regression with a log link was fitted first, treating collision count as the dependent variable and trust change scores as predictors. Dispersion was assessed by comparing the deviance and Pearson chi-square statistics to their degrees of freedom; both ratios substantially exceeded 1, indicating overdispersion relative to the Poisson assumption of equal mean and variance. A negative binomial model, which includes an additional dispersion parameter, was therefore estimated via maximum likelihood. The dispersion parameter was statistically significant, and a likelihood-ratio test indicated that the negative binomial model fit significantly better than the Poisson model. Consequently, negative binomial estimates are reported as incidence rate ratios (IRR) with 95% confidence intervals and serve as the basis for inference about trust–collision associations. Pearson and Spearman correlations involving collision count are retained only as descriptive and robustness summaries.

4. Results

4.1 Demographics

This study involved 41 construction-related professionals and students who completed the human–drone collaboration task in a virtual reality environment. The sample was predominantly male (76.32%), with female representation comprising 23.68%. Racially and ethnically, the sample was diverse, with Non-Hispanic White participants comprising the largest group (58.54%), followed by Non-Hispanic Asian (29.27%), Hispanic/Latino (7.32%) and other backgrounds (4.88%). Age distribution skewed markedly toward younger participants, with 86.84% 18–24-year range, followed by 13.16% aged above 24 years. Work experience in construction-related domains was limited for most; 63.16% reported less than one year of hands-on experience, whereas 36.84% had accumulated more than one year.

4.2 Trust development

Participants' trust in the drone evolved substantially during the collaborative VR construction task (Table 1). Overall trust, measured as the aggregate change across pre- and post-interaction ratings, increased significantly from baseline, $M = 0.25$, $SD = 0.52$, $t(40) = 3.08$,

Table 1. Descriptive statistics and one-sample *t*-test results for trust change measures ($N = 41$)

Variable	M	SD	95% CI lower	95% CI upper	*t* (40)	*p*	Cohen's *d*
Perceived risk	0.21	1.01	−0.11	0.53	1.34	0.188	0.21
Perceived benevolence	0.28	0.81	0.03	0.54	2.24*	0.031	0.35
Perceived competence	0.35	0.80	0.10	0.60	2.80**	0.008	0.44
Perceived reciprocity	0.34	0.80	0.09	0.59	2.73**	0.009	0.43
Change in trust (Delta)	0.25	0.52	0.09	0.41	3.08**	0.004	0.48

Note(s): *$p < 0.05$; **$p < 0.01$. CI = confidence interval. M = mean; SD = standard deviation. One-sample *t*-tests tested whether each trust dimension differed significantly from 0 (no change). Negative values indicate reduced trust; positive values indicate increased trust

Source(s): Authors' own work

$p = 0.004$, Cohen's $d = 0.48$, 95% CI $[0.09, 0.41]$. This finding confirms that the collaborative interaction fostered a meaningful, measurable shift in participants' trust toward the drone. When examined at the dimensional level, the trust increase was driven primarily by three components. Perceived benevolence, the sense that the drone acted with beneficial intent, increased significantly, with $p = 0.031$. Perceived competence also rose substantially, $p = 0.008$, indicating that participants viewed the drone as more capable after working alongside it. Similarly, perceived reciprocity increased significantly, $p = 0.009$. In contrast, perceived risk showed only a small, non-significant change, $p = 0.188$, suggesting that participants did not uniformly perceive a reduction in hazard or threat posed by the drone.

These results indicate that the human–drone collaboration produced substantial gains in benevolence, competence and reciprocity, with all three showing medium-to-large effect sizes. The lack of significant change in perceived risk suggests that while participants grew more confident in and connected to the drone, their assessment of potential dangers remained relatively stable.

4.3 Trust-performance association

The strength of participants' trust in the drone was associated with objective operational performance indicators, namely completion time and collision count in the VR-based construction inspection task. Participants reporting larger increases in trust completed the collaborative construction task significantly faster and with fewer collisions (Figure 3).

For completion time, the Pearson correlation between overall trust change and task duration was negative, $r = -0.60$, $p < 0.001$, indicating that greater increases in trust were associated with faster completion. The Spearman rank-order correlation, $\rho = -0.54$, $p < 0.001$, confirmed this relationship and suggested that the pattern was robust to non-normality and outliers. Participants with larger trust gains tended to complete the task in less time, whereas those with smaller or negative trust change generally required longer completion times. For collisions, the Pearson correlation between overall trust change and collision count was negative, $r = -0.71$, $p < 0.001$ and the Spearman correlation showed a similarly strong association, $\rho = -0.77$, $p < 0.001$. Thus, participants who reported larger trust gains tended to experience fewer safety-relevant errors during human–drone interaction.

To account for the count nature of the collision outcome, collisions were also modeled using a negative binomial specification with a log link, treating collision count as the dependent variable and trust change scores as predictors. Larger trust gains were associated with significantly fewer collisions: the coefficient for overall trust change (Δ) was -0.71 (SE $= 0.12$; $z = -5.83$; $p < 0.001$), corresponding to an incidence rate ratio (IRR) of 0.49 (95% CI $[0.39, 0.63]$). Each one-unit increase in overall trust change was associated with an approximately 51% reduction in the expected collision rate. These count-model results are consistent with the correlation patterns reported above and provide outcome-appropriate

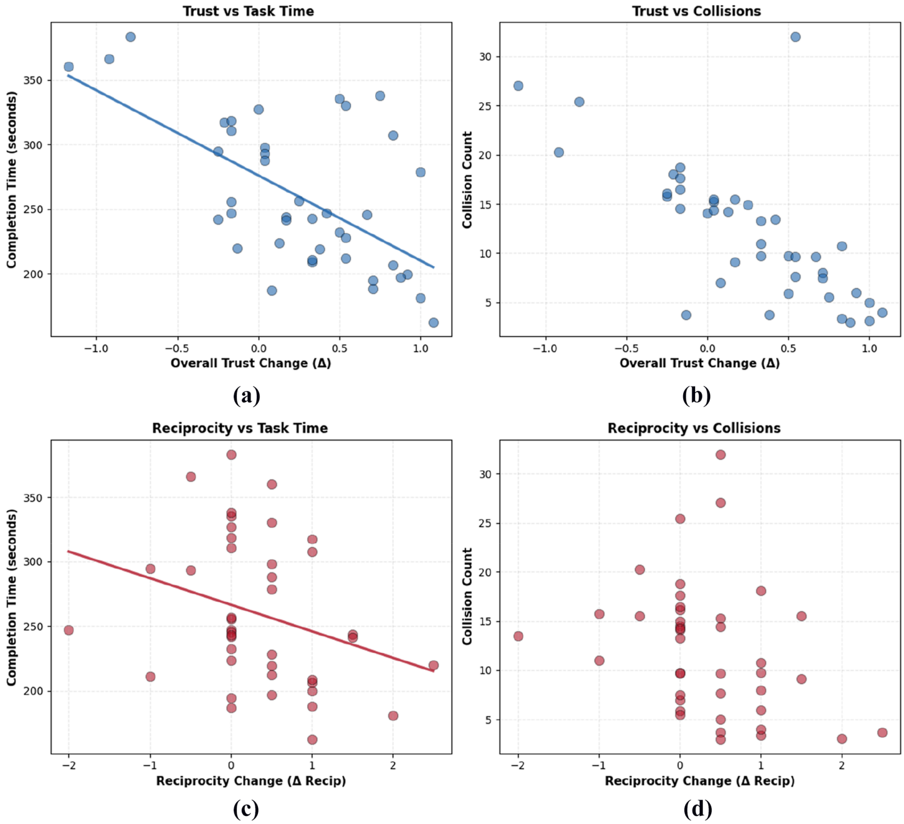

Figure 3. Associations between trust measures and task performance in the VR-based drone inspection task. (a) Overall trust change (Δ) versus completion time. (b) Overall trust change (Δ) versus collision count. (c) Reciprocity change (Δ Recip) versus completion

evidence that greater trust gains were associated with fewer safety-relevant errors in this task. Pearson and Spearman coefficients involving collisions are therefore interpreted as descriptive and robustness summaries, with formal inference based on the negative binomial model.

4.4 Association of trust dimensions with performance outcomes

To clarify which specific facets of trust are most associated with the overall trust-performance relationship, correlations between each trust dimension and objective performance were examined separately. This dimensional analysis revealed important distinctions in how different trust components influence outcomes. Reciprocity emerged as the trust dimension most consistently linked to safer task performance (Table 2). For collision count, reciprocity showed a significant negative Pearson correlation, $r = -0.32$, $p = 0.041$, and this relationship was strengthened and clarified in the Spearman analysis, $\rho = -0.40$, $p = 0.010$. Participants who experienced greater increases in perceived reciprocity, a sense that the drone responded to their actions in a coordinated, mutually supportive fashion, consistently made fewer collisions. Additionally, reciprocity showed the largest (though marginally non-significant) association with completion time in the Pearson analysis, $r = -0.29$, $p = 0.068$, and reached statistical significance in the Spearman analysis, $\rho = -0.37$, $p = 0.019$. This pattern suggests that, among the dimensions examined, reciprocity change shows the most consistent bivariate association with performance in this task.

Table 2. Contribution of trust dimensions to task performance

Trust dimension	Completion time (Pearson)	Completion time (Spearman)	Collision count (Pearson)	Collision count (Spearman)	Performance relevance
Trust (Delta)	$r = -0.60^{**}$	$\rho = -0.54^{**}$	$r = -0.71^{**}$	$\rho = -0.77^{**}$	High (both metrics)
Perceived risk	$r = -0.26$	$\rho = -0.29^{\dagger}$	$r = -0.41^{**}$	$\rho = -0.52^{**}$	Moderate (collisions)
Perceived benevolence	$r = -0.17$	$\rho = -0.07$	$r = -0.26$	$\rho = -0.26$	Weak
Perceived competence	$r = -0.08$	$\rho = -0.12$	$r = -0.02$	$\rho = -0.12$	Negligible
Perceived reciprocity	$r = -0.29^{\dagger}$	$\rho = -0.37^{*}$	$r = -0.32^{*}$	$\rho = -0.40^{**}$	High (both metrics)

Note(s): †$p < 0.10$, *$p < 0.05$, **$p < 0.01$. Two-tailed tests. r = Pearson correlation coefficient; ρ = Spearman rank-order correlation coefficient

Source(s): Authors' own work

Perceived risk demonstrated a moderate negative association with collisions in the Pearson analysis, $r = -0.41$, $p = 0.008$, and this relationship remained robust in the Spearman correlation, $\rho = -0.52$, $p = 0.001$. However, risk showed a weaker and non-significant association with completion time, $r = -0.26$, $p = 0.096$; Spearman $\rho = -0.29$, $p = 0.068$. This mixed pattern suggests that reduced perceived risk may contribute to safer interaction but has less influence on task speed. Benevolence and competence, despite showing significant pre-post gains in the dimensional trust analysis, demonstrated weak and largely non-significant associations with performance outcomes. Benevolence correlated minimally with collisions, $r = -0.26$, $p = 0.103$, and completion time, $r = -0.17$, $p = 0.293$. Competence showed negligible relationships with both metrics, $r = -0.02$ for collisions, $p = 0.906$, and $r = -0.08$ for completion time, $p = 0.625$. While both dimensions increased trust, neither uniquely explained substantial variance in objective performance in this task.

The count-model analysis supports the dimensional correlation pattern for reciprocity. In the negative binomial model, higher reciprocity change was associated with fewer collisions: the coefficient for Δ Recip was -0.26 (SE $= 0.11$; $z = -2.29$; $p = 0.022$), yielding an IRR of 0.77 (95% CI [0.62,0.96]). In other words, each one-unit increase in reciprocity change was associated with an approximately 23% reduction in the expected collision rate. This count-based result aligns with the correlation pattern and indicates that reciprocity retained a meaningful association with collision avoidance when collisions were analyzed as a count outcome. Figure 3 visually summarizes the associations between overall trust change, reciprocity change and task performance in the VR-based construction drone task. Panels (a) and (c) display the relationships between trust/reciprocity and completion time, with least-squares lines shown as visual aids for the negative correlations. Panels (b) and (d) show the observed collision counts for each level of overall trust change and reciprocity change without fitted lines, emphasizing the discrete, count nature of the collision outcome.

Among the four trust-related dimensions, reciprocity emerged as the trust dimension most associated with safer task performance, consistently relating to fewer collisions and faster task completion. Risk contributes secondarily to collision avoidance, while benevolence and competence, though part of overall trust growth, do not show direct linkage to the specific performance metrics measured in this human–drone construction assembly task. These exploratory associations suggest that reciprocal responsiveness may be a useful direction for future research on drone interaction design, though experimental studies are needed before drawing design or training recommendations. Figure 4 presents the Pearson correlation matrix for trust change dimensions, overall trust change (Δ) and

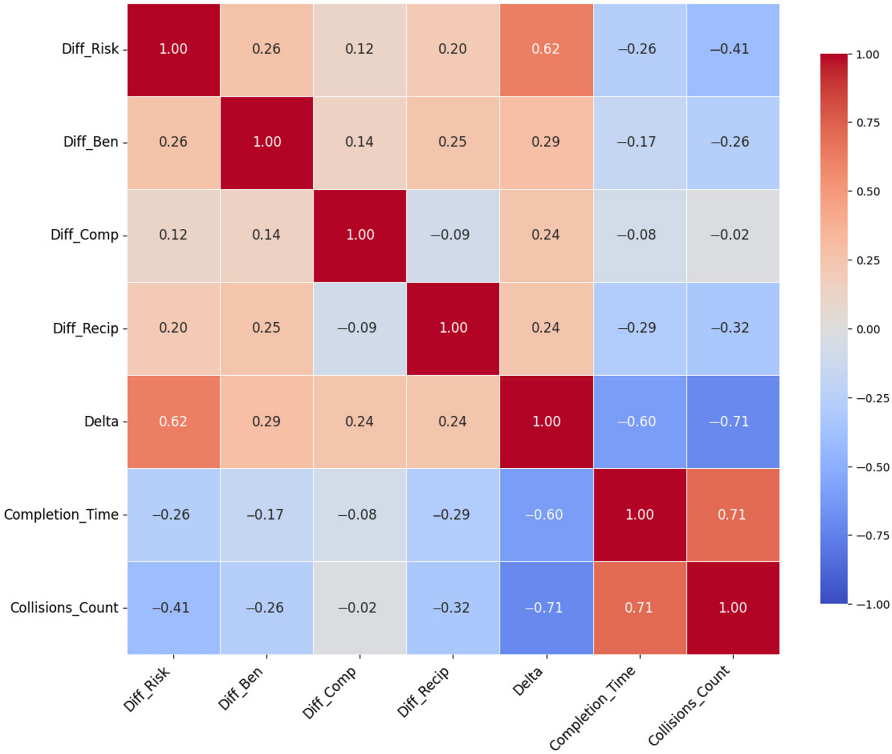

Figure 4. Correlation heatmap for trust dimensions and task performance. Source: Authors' own work

performance outcomes (completion time and collision count), where each Diff_variable represents a post-pre trust difference for that dimension. The warmer cells indicate positive correlations and cooler cells indicate negative correlations. The matrix highlights negative correlations between overall trust change and both completion time and collisions, as well as a notable negative association between reciprocity and collision count. In contrast, benevolence and competence exhibit comparatively weak relationships with the performance measures, underscoring the differential relevance of specific trust facets.

5. Discussion

This study examined how trust in drone develops through collaborative interaction in a VR construction environment and how specific trust dimensions relate to objective performance outcomes. The findings show that (a) overall trust and three trust dimensions, benevolence, competence and reciprocity, increase significantly following the collaborative task, (b) higher trust is associated with faster completion times and fewer collisions, and (c) among the measured dimensions, reciprocity and, to a lesser extent, perceived risk are most directly related to objective performance, whereas benevolence and competence are not. The increase in overall trust after the VR-based inspection task indicates that even a short, task-focused collaboration can shift operators' trust in drones. This aligns with broader HRI sign that trust is not fixed but dynamically shaped by interactions, particularly when people directly observe the system's behavior under conditions of uncertainty and risk (Chang and Hasanzadeh, 2024).

5.1 Trust and performance: overall and dimension-specific effects

The negative correlations between overall trust change and both completion time and collisions suggest that trust is not merely an attitudinal outcome but is also associated with operational performance. Participants who emerged from the task with higher trust completed the inspection more quickly and with fewer collisions, indicating more efficient and safer human–drone collaboration. This is consistent with theoretical accounts that conceptualize trust as a regulator of reliance: when operators appropriately trust the system, they can offload certain control decisions, maintain focus on higher-level goals and avoid overcautious or erratic interventions that introduce inefficiencies and errors (Chang and Hasanzadeh, 2024). Reciprocity consistently shows a bivariate association with performance, with increases in perceived reciprocity linked to fewer collisions and faster completion times. This study was designed to capture initial trust calibration during a collaborative task, which means the reciprocity–performance association is best understood as correlational rather than directional; therefore, the pattern aligns with an interpretation of beneficial reliance rather than complacency. However, because the task did not include engineered failures or rare high-consequence events, the study does not address conditions under which high trust might lead to insufficient monitoring or catastrophic errors; examining this trade-off will require future experiments that manipulate failure events and monitor checking behavior explicitly.

Perceived risk shows a moderate negative relation with collisions, though not with task speed. Participants who reported larger reductions in perceived risk tended to experience fewer collisions, suggesting that feeling less threatened by the drone may free operators to maneuver more fluidly and confidently around obstacles without overreacting. At the same time, the lack of a relationship with completion time indicates that lowering perceived risk alone does not necessarily translate into faster execution; operators can be cautious yet effective, particularly when reciprocity is high. In contrast, benevolence and competence, despite growing significantly during the task, display weak and non-significant associations with performance metrics. This suggests that, within the specific context of a relatively constrained inspection flight, perceiving the drone as well-intentioned or technically capable is not sufficient, by itself, to drive measurable improvements in speed or collision avoidance once a basic threshold of acceptability is met. One interpretation is that competence and benevolence function as foundational enablers of trust, necessary for operators to be willing to engage with the system at all, while reciprocity and risk more directly govern fine-grained behavioral coordination and safety-relevant decisions. Therefore, trust is an indicator of performance, but the mechanisms through which trust translates into operational outcomes are unevenly distributed across dimensions. Overall, these results do not support a uniform ‘more trust is always better’ view; instead, they indicate that reciprocity and perceived risk are the performance-relevant dimensions, whereas benevolence and competence play more attitudinal or foundational roles in this task context. These findings shift the focus from the broad question of whether trust in automation matters to the more specific question of which trust dimensions, derived from human–technology trust models, are most consequential for safety and efficiency in construction-relevant drone operations.

5.2 Implications for drone system design, training and organizational practice

The prominence of reciprocity as a performance-relevant dimension suggests potential implications for the design of autonomous drone systems in construction. For construction managers and system designers, the association between reciprocity and fewer collisions indicates that interaction design may benefit from prioritizing responsive behaviors that make the drone’s adjustment to operator input transparent. Training protocols could be structured to help operators practice these reciprocal patterns, such as synchronizing inputs with drone motion, anticipating system responses and learning to recognize when the system is not responding as expected, thus targeting the operator–system coordination processes reflected in the reciprocity dimension rather than immutable social traits. From a construction education perspective, VR-based drone tasks provide a controlled setting to calibrate students' trust before they work with physical drones on active sites. Instructors can use repeated VR scenarios to assess baseline trust profiles, deliberately vary drone responsiveness and transparency and facilitate debriefings that highlight how different trust levels and interaction patterns affect collisions and task efficiency. Such modules can help students learn to develop neither blanket distrust nor complacent over-trust, but calibrated reliance that aligns with the system's capabilities, thereby preparing them for safer operation of real, costly and potentially dangerous equipment.

Interfaces and control policies should be optimized not only for accuracy and stability but also for legible and contingent responsiveness to operator inputs. Examples include smooth, predictable transitions between manual and autonomous modes that visibly acknowledge the operator's commands, trajectory planning that clearly reflects user-specified priorities and feedback mechanisms that signal how the drone is taking the operator's actions into account in real time. Such features can enhance the operator's reciprocity, thereby improving collision avoidance and task flow. For training programs, the results suggest that beyond technical flight skills, curricula should explicitly cultivate patterns of reciprocal interaction. Scenario-based VR training can be structured so that operators learn to coordinate timing, anticipate drone responses and experiment safely with different levels of reliance. Debriefing can highlight how specific behavior patterns affect both trust and performance. Because risk perceptions change slowly, consistent exposure to stable, predictable behavior in varied but controlled conditions may be necessary to gradually recalibrate perceived risk while maintaining appropriate caution. At the organizational level, the findings underscore that successful integration of drones on construction sites cannot be addressed solely through hardware procurement and basic certification. Policies governing roles, responsibilities and intervention thresholds should align with how operator trust develops and functions in practice. For instance, defining clear rules for when the drone may autonomously adjust its path, when operators are expected to override and how conflicts are resolved can support more stable trust trajectories and reduce misuse or disuse. Emphasizing mutual responsiveness in vendor selection criteria and system acceptance testing may also lead to safer and more productive deployments.

This study contributes to the broader HRI and construction automation literature by providing empirical indication that trust in an autonomous aerial robot can meaningfully increase over the course of a single collaborative task conducted in a realistic, high-workload construction simulation, demonstrating the feasibility of VR environments as testbeds for trust development. Second, it moves beyond global trust scores by examining four distinct trust dimensions and showing that they do not contribute equally to performance in this task. The identification of reciprocity as showing the most consistent bivariate association with performance in this context complements prior work that has emphasized competence as a primary contributor to trust formation, suggesting that once basic competence is established, interactive qualities related to mutual coordination may also be relevant to operational outcomes. Third, the study focuses specifically on construction-oriented drone operations, addressing a domain where trust has been recognized as important but empirically underexplored. The use of objective performance indicators, completion time and collision count, provides a direct link between psychological constructs and performance metrics that matter to practitioners. This helps bridge the gap between conceptual discussions of trust and future research that can inform system design, training and management practices in the construction industry. Given that the analyses are based on bivariate correlations and single-task count models in a VR inspection scenario, these findings should be interpreted as preliminary, context-specific evidence rather than predictive models or generalizable claims about safety improvement.

5.3 Limitations

First, this study captured trust at two time points surrounding a single collaborative task, focusing specifically on initial trust calibration, the shift from expectation-based to experience-based trust that occurs when operators first work directly with an autonomous drone. This design choice addresses a distinct important question: Which trust dimensions respond to initial collaborative exposure, and which of those dimensions associate performance even in first encounters? Prior HRI research confirms that initial trust formation occurs rapidly and meaningfully during first interactions (Cameron *et al.*, 2015; Robinette *et al.*, 2016), with effect sizes comparable to those observed in this study. These initial trust shifts are consequential because they shape subsequent reliance patterns, frame operator expectations for future interactions and inform the design of onboarding protocols where extended acclimatization is often impractical. However, the single-session design cannot address trust stability, long-term trajectories or responses to system failures across varied conditions. Longitudinal designs following operators through multiple sessions, diverse task contexts and critical incidents (e.g. near-misses, malfunctions) are needed to examine how dimensional trust evolves over time, whether reciprocity remains the dominant performance predictor as competence expectations stabilize and how trust repair mechanisms function after violations. Second, the study employed a single type of collaborative task with one level of automation and relatively constrained mission objectives. Different task types, higher or adaptive autonomy levels or multi-drone scenarios may elicit different trust dynamics and alter the relative importance of specific trust dimensions. Reciprocity in this study reflects perceived mutual responsiveness within a low-level shared-control loop, which is more limited than the richer forms of mutual adaptation sometimes discussed in HRI with highly autonomous agents. Future work with controllers that implement higher-level autonomous adaptation could examine whether this stricter form of reciprocity shows similar or stronger associations with performance. Third, the sample consisted primarily of students and early-career individuals with limited construction experience, which may restrict generalizability to experienced drone pilots or field supervisors who operate under time pressure, organizational constraints and risk exposure.

Trust was assessed via self-report before and after the task, which captures conscious evaluations but may miss fast, implicit adjustments occurring within the task. Integrating continuous or event-based trust measurement (e.g. physiological indicators, real-time confidence ratings or behavioral proxies such as voluntary reliance) would provide a more fine-grained picture of trust dynamics. Additionally, while multiple correlations were examined across dimensions and performance metrics, analyses were exploratory and not corrected for multiple comparisons; in this design, pre-post change scores provide a simple summary of trust development over time and are used primarily for descriptive and exploratory analyses alongside change in trust levels, and more complex approaches (e.g. longitudinal or polynomial response-surface models) would be more appropriate in larger samples with multiple measurement waves, particularly when the focus is on discrepancies between simultaneous constructs such as perceived versus objective performance; replication in larger samples is needed to confirm the robustness of the observed effects, particularly for marginal associations such as reciprocity with completion time.

For the collision count outcome, negative binomial regression was used as the primary analytic approach given confirmed overdispersion relative to the Poisson model; Pearson and Spearman correlations involving collisions were retained only as descriptive and robustness summaries. Given the modest sample size, these count-model estimates should be interpreted as preliminary, and replication in larger samples is needed to obtain more precise rate estimates and to test additional predictors of collision risk. Finally, the drone's behavior in this study was not explicitly optimized for reciprocity; rather, reciprocity emerged from participants' subjective interpretations of its responsiveness under a fixed control policy. Future work could manipulate reciprocity more directly, for example, comparing fixed, minimally responsive controllers to adaptive controllers that adjust to operator behavior and test causal effects on both trust dimensions and performance. Overall, the results suggest that trust, and reciprocal responsiveness in particular, is associated with how safely and efficiently human operators performed in this VR-based drone task, rather than functioning only as a general attitude.

Examining trust as separate dimensions, rather than as a single undifferentiated construct, may offer a more targeted starting point for future engineering, training and organizational research.

6. Conclusion

This study examined how distinct dimensions of trust relate to objective performance in VR-based construction drone inspection tasks. Using a within-subjects design, trust in the drone was measured before and after the collaborative inspection task across four dimensions, namely perceived risk, benevolence, competence and reciprocity, and related to task completion time and collision count. The results show that collaborative task significantly increased overall trust ($d = 0.48$), with benevolence, competence and reciprocity all showing medium-to-large gains, while perceived risk remained stable. This pattern suggests that collaboration can shift operator attitudes toward capability and responsiveness without immediately altering risk assessments. Second, trust change was also associated with performance: operators with larger increases in trust tended to complete tasks faster and experienced significantly fewer collisions, with the negative binomial model indicating an approximately 51% reduction in the expected collision rate per unit increase in overall trust change. These findings shift the focus from the broad question of whether trust matters to the more specific question of which dimensions of trust matter, and in relation to which performance outcomes. Based on these exploratory associations, interaction designs that foster reciprocity and training approaches that address risk perception may be worth examining in future experimental research, rather than relying on demonstrations of system competence alone. For researchers, these findings suggest that optimizing autonomous construction technologies may require attention not only to technical performance but also to the human coordination patterns that appear to relate to safety and productivity on dynamic jobsites. As construction increasingly relies on human–robot teams, further research on which dimensions of trust matter, and how they can be fostered, may help clarify the conditions under which these technologies can be deployed effectively. By measuring trust dimensionally and linking these measures to objective safety and efficiency metrics, this study moves beyond global trust scores to offer preliminary, exploratory evidence on which trust dimensions may be most relevant to system design and operator training; these associations should be confirmed through future experimental research before informing specific design or training decisions.

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