PROJEKTNR. 14110

# AI Factory/Construction

Slutrapport

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[Lägg till logotyper]

# Innehållsförteckning

# Sammanfattning

Detta forskningsprojekt har syftat till att utforska hur digitala verktyg och AI kan stötta beslutsfattande för platsledningen på en byggarbetsplats. Effektivt beslutsfattande är avgörande för att hantera framdriften på byggarbetsplatser där platschefen har ett stort ansvar för en mängd olika aktiviteter som tillsammans ska bidra till projektets mål. Kritiska beslut för detta kan tex innehålla tekniska, ekonomiska, tidsmässiga, logistiska eller säkerhetsmässiga aspekter. Ett effektivt beslutsfattande kräver bland annat tillgång till korrekt och aktuell information, liksom förmågan att analysera denna. Digitalisering och AI har stora förutsättningar att bidra med detta, och har inte utnyttjats lika väl inom byggbranschen som i andra industrier.

Projektet har utforskat ett antal möjliga användningsfall där befintlig teknik i olika kombinationer skulle kunna bidra med ett stärkt beslutsstöd. Dessa användningsfall identifierades genom semistrukturerade intervjuer till: Armeringsstål, Byggnadsställningar, Erfarenhetsåterföring, Hälsa och säkerhet, samt Optimerad planering. För samtliga fall har tänkbara kombinationer av teknik föreslagits och för ett användningsfall (Byggnadsställningar) har tekniken utvecklats testats och demonstrerats genom en prototyp. Den tekniska lösningen bygger på skanning med hjälp av LiDAR (Light Detection and Ranging) till ett punktmoln som genererar en modell av byggnadsställningen. Vidare har ett flertal algoritmer utvecklats för att dels extrahera och identifiera objekt i modellen, dels jämföra ursprunglig modell med modeller där förändringar skett, dels jämföra modellen med regelverket för konstruktionen. Slutligen har VR- och AR-teknik använts för att presentera och tillgängliggöra informationen för platsledningen. Demonstrationer för och intervjustudier med företagsrepresentanter har sedan används för att utvärdera prototypens förmåga att bidra till beslutsstöd i en operativ verksamhet.

Resultatet tyder på att digitalisering och AI-stöd kan bidra till ett effektivare mer informerat beslutsfattande på en byggarbetsplats. Den genomförda studien med prototyp för byggnadsställningar visar på att detta kan bidra till:

- förbättrad säkerhet och efterlevnad;
- effektivare inspektioner;
- ökad förmåga till informerat beslutsfattande;
- teknisk möjlighet att skala och anpassa för olika byggarbetsplatser;
- förbättrad operativ effektivitet

Studien visar också att det finns en positiv inställning till denna typ av teknikstöd, men att de tekniska hjälpmedlen kontinuerligt behöver påvisa sin pålitlighet för att skapa nödvändig tillit, liksom att de konkreta besluten inte kan överlåtas åt AI-verktyg, utan att det är människor som fattar beslut, där AI och annan teknik kan ge ett starkt stöd i den processen.

# Förord

Forskargruppen vill tacka organisationer, företag och individer inom byggsektorn för deras generösa stöd under hela forskningsprocessen, särskilt när det gäller att dela med sig av sin tid, expertis och erfarenheter under projektet. Ett särskilt tack till SBUF (Svenska byggbranschens utvecklingsfond) och det strategiska innovationsprogrammet Smart Built Environment för finansiering, samt NCC och HÖ Allbygg för deras stöd och bidrag genom hela projektet.

Forskningsprojektet har letts av professor Ramin Karim, LTU. Övriga medverkande i projektet har varit: Amit Patwardhan, Sameer Prabhu, Kajsa Simu och Olle Samuelson, samtliga från LTU. I den första fasen medverkade även Gaurav Sharma, LTU.

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# 1 AI och digitalisering i byggbranschen

Processen för planering, projektering och byggande är informationsintensiv och präglas av ”många-till-många” relationer i informationsutbytet mellan de olika aktörerna. Att hantera och bearbeta information och omsätta denna till praktisk kunskap är en framgångsfaktor för ett byggprojekt. Att ha rätt kunskap och information vid varje given tidpunkt ger förutsättningar för ett beslutsfattande som ökar förutsägbarheten, minskar riskerna och därigenom bidrar till ökad produktivitet och effektivitet. Detta gäller inte minst i själva byggprocessen, det vill säga produktionsfasen i samhällsbyggnads-processen. Digitalisering och artificiell intelligens (AI) har möjligheter att stödja informationshanteringen och därmed skapa förutsättningar för bättre beslutsfattande, planering, logistikhantering och utförande, samt att skapa ett strukturerat lärande (Regona et al. 2022), något som är underutnyttjat i produktionsfasen idag.

Byggföretag använder idag digital teknik inom flera delar av verksamheten, såväl inom stödfunktioner som ekonomi och administration, liksom i kärnverksamheten i arbetsmoment som tid- och resursplanering, logistik, 3D-modellering, ledning och uppföljning samt inom arbetsmiljö och i säkerhetsarbetet. Digitaliseringen och användningen av AI har dock inte kommit lika långt i byggbranschen som i andra industrier (Soori et al 2024). Tillämpningar av AI inom byggprocessen sker ännu på låg nivå, men med ett stigande intresse. Samuelson (2023) visar i en kartläggning av utvecklingsinitiativ att AI och Maskininlärning utgör cirka 15 % av gemensamma forsknings- och utvecklingsprojekt i byggbranschen, men med indikationer på att detta har ökat de senaste åren och kan förutsättas fortsätta öka.

Ett begränsat utnyttjande och otillräcklig integration av digital teknologi är ett hinder för utveckling och implementering av AI i produktionsfasen inom byggbranschen (Engström et al.,2021). Fokus i byggbranschen har i fler fall legat på att hitta unika digitala lösningar inom ramen för olika specialistområden. Ett annat hinder i den digitala utvecklingen inom byggbranschen är den projektfokuserade strukturen och kulturen, och den suboptimering som det innebär. Tilltron till individers förmåga och exempelvis platsledningens erfarenhet och kunskap är både en styrka, och en stor svaghet för ett företag då förmågan att dela kunskap och erfarenhet mellan projekt och individer är begränsad (Simu, 2009).

Rollen som platschef för en byggarbetsplats är utmanande och kräver förmåga att ta hänsyn till många aspekter under ett byggprojekt, såsom: säkerhet, kostnader, tidplanering, standarder och föreskrifter, osäkerheter och risker (Styhre & Josephson, 2006; Gómez et al. 2023). Digital teknik och AI kan möta dessa utmaningar genom att förbättra förmågan att samla in data och information från den fysiska verkligheten liksom från olika underlag och källor och sedan bidra med analyser, prediktioner och beslutsstöd. I förlängningen bidrar detta till kontinuerliga förbättringar för produktionsstyrningen och skapar nytta på individ-, projekt- och företagsnivå (Regona et al. 2022).

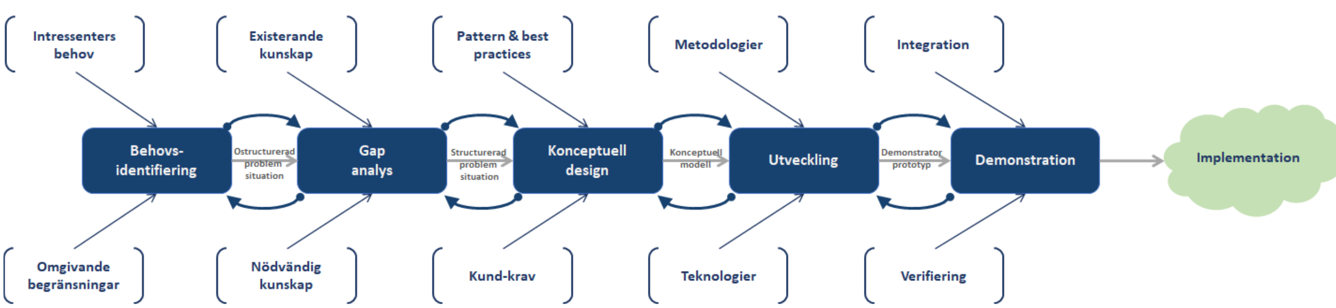
Detta projekt har syftat till att undersöka möjligheten att utveckla och använda digitala verktyg och AI som stöd för beslutsfattande för platsledningen på en byggarbetsplats inom ett antal olika konkreta användarfall. Syftet har också varit att utveckla prototyper till någon eller några av dessa användarfall och genomföra konkret test och utvärdering av en sådan prototyps förmåga att bidra till stöd för beslutsfattande.

# 2 AI Factory for CONSTRUCTION (AIF/C)

AI Factory är ett övergripande koncept som syftar till att stödja olika branschers utveckling genom digitisering, digitalisering och digital transformation. Järnvägar, gruvdrift, flyg, processindustri och bygg är de pågående projekten inom AI Factory (Karim et al., 2023). Detta projekt har fokuserat på möjliga byggrelaterade tillämpningar och har därmed fått namnet AI Factory for Construction (AIF/C).

Digitaliseringen har avsevärt förbättrat affärsverksamheten, processerna och produktiviteten inom flera sektorer de senaste decennierna, och lett till ökad lönsamhet, effektivitet och säkerhet. Framsteg inom digital teknik, särskilt artificiell intelligens (AI), förändrar tillverkningsindustri, telekom-industri och detaljhandel, till exempel genom teknik som maskininlärning, robotteknik och kunskapsbaserade system. AI kommer att ha en betydande inverkan på hur uppgifter utförs i olika branscher och erbjuder nya sätt att öka produktiviteten och lösa olika typer av utmaningar.

AIF/C tillämpar en strukturerad metodik för framdriften av projektets aktiviteter, se figur 2.1. Det är en agil process med ett antal iterativa steg som där varje stegs resultat och lärdomar utnyttjas som input till nästa steg. Processen bidrar till succesiv utveckling inom projektet och till att de förväntade resultaten kan uppnås.




**Figur 2.1. AIF/C:s strukturerade agila process för genomförande**

AI Factory består av en uppsättning så kallade ”Line-of-production” (LoP), vilket utgörs av konfigurerbara digitala komponenter (hård- och mjukvara) som består av specialiserade databehandlingssteg. Dessa utformas och implementeras baserat på mikrotjänster (micro-services) som kan bestå av t.ex. algoritmer. AI Factory´s mikrotjänster implementeras baserat på en distribuerad datormetod för att tillgodose kraven för respektive LoP. Detta för att möte det enskilda industriella sammanhanget och behovet.

Det övergripande behovet som identifierats för AIF/C är att stötta effektivt beslutsfattande för platsledningen på en byggarbetsplats. Detta har sedan inom projektet genomförande brutits ned till olika konkreta användarfall där beslutsfattande är kritiskt och där digitalt stöd potentiellt kan bidra till effektivisering.

Effektivt beslutsfattande är avgörande för att hantera byggarbetsplatser, där platschefen har ansvar för en mängd olika aktiviteter som tillsammans ska leda byggprojektet framåt. Byggplatschefer har stort fokus på kritiska beslut relaterade till tekniska, ekonomiska och säkerhetsmässiga aspekter. Beslutsfattande är här en dynamisk process som bygger på byggplatspersonalens samlade erfarenhet och kunskap. En mängd faktorer styr dessa beslut.

Målgruppen för projektet är dels företag i byggindustrin, dels utvecklare av hård- och mjukvaruverktyg. Projektet bidrar också till att flytta fram forskningsfronten inom tillämpad AI för byggindustrin.

# 3 Projektets genomförande och resultat

Artificiell intelligens (AI) och digitalisering kan förändra byggbranschen bland annat genom att förbättra beslutsprocesser och därmed öka effektiviteten och minska risker. I detta projekt utforskades hur AI och digital teknik kan stödja och hjälpa byggplatschefer att fatta komplexa beslut. Befintliga utmaningar identifierades och modeller som integrerar hårdvara med AI-verktyg och algoritmer användes för att förbättra beslutsfattandet.

## 3.1 Användningsfall

Projektet inleddes med att tillsammans med de medverkande entreprenadföretagen identifiera ett antal möjliga användningsfall och att prioritera vilket eller vilka användningsfall projektet skulle fokusera på. Med utgångspunkt från projektets syfte, att nyttja AI och digital teknik för att stötta platsledningen i det dagliga beslutsfattandet, genomfördes en studie med semistrukturerade intervjuer med platschefer och arbetsledare, som representerade två pågående entreprenaders byggarbetsplatser. Fem tänkbara användarfall identifierades och dessa beskrivs nedan kort utifrån dess utmaningar, kopplat till beslutsfattande.

- **Armeringsstål**: Innan gjutning behövs en verifiering och ett godkännande av att armeringen är korrekt utförd enligt konstruktionshandlingarna, vilka kan utgöras av ritningar, armeringsspecifikationer och/ eller BIM-modeller. De viktiga kriterierna att verifiera är armeringsstängernas diameter, antal och positionering.
- **Byggnadsställningar**: Platschefen har ansvar för att byggnadsställningarna vid varje tillfälle är korrekt monterade och följer det regelverk för ställningar som finns. Platschefen inspekterar och

godkänner de uppförda ställningarna samt kontrollerar löpande manuellt att inga avvikelser föreligger, och att ställningarna uppfyller säkerhetskraven.

- **Erfarenhetsåterföring**: Historiska data och lärdomar från tidigare projekt finns inte systematiskt samlade och är därmed inte lätt tillgängliga. Detta leder till ineffektivitet i kunskapsöverföringen eftersom varje nytt projekt består av en ny sammansättning av projektteamet. Även för den data som finns är det tidskrävande att söka rätt på aktuell information vid varje givet tillfälle.
- **Hälsa och säkerhet**: Att säkerställa personalens hälsa och säkerhet i utsatta områden med hög risk är utmanande. Det finns både tekniska och integritetsmässiga svårigheter med att kontrollera personers placering i realtid på en stor byggarbetsplats. Vissa platser är av erfarenhet mer utsatta och riskfyllda än andra, men det går förstås inte att förutsäga var och när olyckor inträffar.
- **Optimerad planering**: Att optimera tid- och resursplanering samt att göra träffsäkra kalkyler för utfall är en komplex och svår uppgift. Dels kräver det mycket insamlad data om rådande status på byggarbetsplatsen, vilket ska jämföras med handlingar, tidplaner och budget. Dels är många aktiviteter sammankopplade i komplexa samband som kan vara svåra att överblicka.

För att ta adressera dessa utmaningar föreslås olika konceptuella modeller. För användningsfallet med *armeringsstål* föreslås LiDAR (Light Detection and Ranging) som kan skanna armerings-stängernas diameter, position och antal, och skapa en modell i form av ett punktmoln. Detta kompletteras med AI-algoritmer som jämför skannade punktmolnsdata med byggnadsinformations-modellen (BIM) vilket sedan kan ge platschefen ett stöd när beslutet ska fattas om gjutningen kan påbörjas eller ej.

Liknande teknik kan användas för användningsfallet *byggnadsställningar*. Genom LiDAR-skanning kan en punktmolnsmodell skapas vid varje önskat tillfälle som sedan med hjälp av AI-algoritmer jämför, dels med den ursprungliga modellen av byggnadsställningen, dels mot det rådande regelverket. Vid projektets medverkan på konferensen AI in AEC i Helsingfors 20-21 mars 2024 konstaterades också att fokus på LiDAR och 3D-punktmolnsdata i forskningen var lågt och att det finns ett behov av ökad expertis inom området för tillämpningar inom byggrelaterad AI.

För användningsfallet *erfarenhetsåterföring* föreslås en språkmodell av inspirerad av ChatGPT. En sådan modell, kallad ”ChatCON” med fokus på byggandet skulle kunna tränas på historiska projektdata för att sedan ge snabb åtkomst till svar på olika typer av frågor och därmed minimera manuella dokumentsökningar.

Användningsfallet *hälsa och säkerhet* kan adresseras med hjälp av bärbar utrustning som smarta västar, hjälmar och likande enheter som möjliggör spårning av personal i realtid. Tillsammans med AI-algoritmer kan dessa bidra till analyser och bedömningar av säkerhetsrisker kopplat till platser och beteenden.

*Optimerad planering* kan uppnås genom AI-lösningar som utnyttjar historiska data för att förutsäga kostnadsprognoser och för att optimera tid- och resursplanering.

Tre av användningsfall valdes ut och analyserades mer utförligt avseende genomförbarhet relaterat till potentiell nytta: *Armeringsstål*, *byggnadsställningar* och *optimerad planering*. Alla tre adresserar konkreta problem som uppstår i en platschefs vardag. De tre användningsfallen och de föreslagna teknikerna enligt ovan presenterades för utvalda personer från de två företagen vid en gemensam workshop med syfte att tillsammans komma fram till prioriterade användningsfall att genomföra inom projektet. Användningsfallet med armeringsstål bedömdes kunna skapa stor nytta, men ansågs samtidigt vara komplext, med svårigheter både att fånga den nödvändigt höga detaljeringsgraden vid en LIDAR-skanning och att förhålla sig till det omfattande regelverket. På samma sätt bedömdes användningsfallet med optimerad planering innebära stora utmaningar relaterat till datainsamling samt integration mellan flera intressenter. Byggnadsställningar valdes som prioriterat användningsfall där potentialen att överbrygga stora säkerhetsrisker är hög, liksom att genomförbarheten med den föreslagna tekniken bedömdes god.

## 3.2 Bedömning av byggställningars status

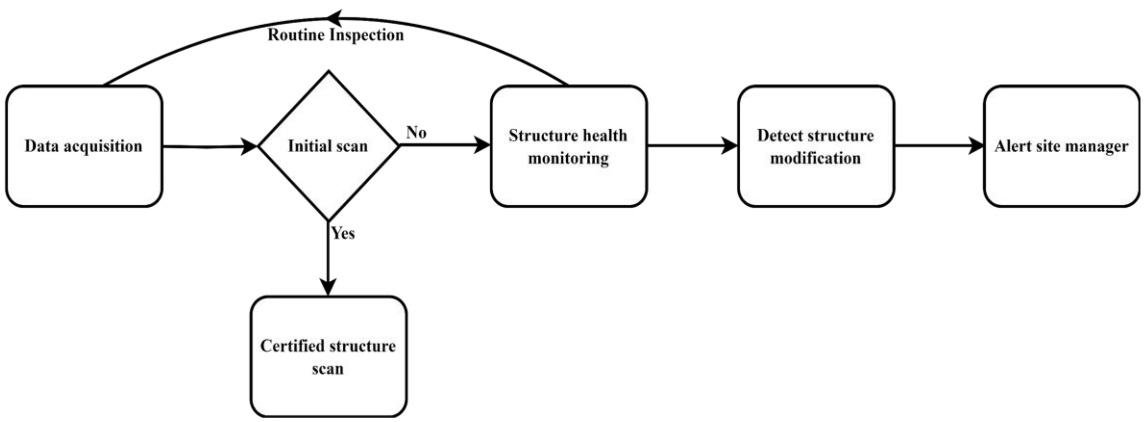
Byggbranschen står för nästan hälften av alla industriolyckor i Sverige, och säkerhet är därför ett högt prioriterat område inom branschen. En stor andel av byggarbetsplatser har byggnadsställningar som används för att byggnadsarbetarna ska ha god och säker tillgänglighet till alla delar av den byggnad som håller på att uppförs. Byggnadsställningar som temporära konstruktioner innebär dock risker för de människor som befinner sig på och i närheten av de tillfälliga konstruktionerna.

Enligt intervjuer med platscheferna utförs inspektion traditionellt av ställningarna helt manuellt. En större byggarbetsplats har många ställningar som tillsammans utgör en komplex anläggning, och de visuella inspektionerna blir då tidskrävande. Ställningarna utsätts under byggtiden för väder och vind som kan påverka dem, liksom att ställningarna också modifieras för att skapa tillgänglighet till exempel för materialleveranser. Detta medför risker för att kritiska delar saknas, att ställningen rörts sig eller att förhållanden ändrats för markstödet, vilket påverkar yrkesarbetarnas säkerhet. För att möta denna utmaning föreslås en lösning med LiDAR-skanning och AI-algoritmer för att automatisera inspektioner av ställningar. Målet är att upptäcka saknade eller avvikande ställningselement och även säkerställa överensstämmelse med konstruktionsreglerna.

Ett strukturerat arbetsflöde för kontinuerlig inspektion av ställningar som stöd till platschefens beslutsfattande består av flera steg.

- **Offsetgenerering**: När en ställning monteras och överlämnas till drift på byggarbetsplatsen kontrolleras och verifieras att den följer alla konstruktionsregler. Ställningen skannas då initialt och bildar en första modell med punktmolnsdata. I den här rapporten kallas de initiala LiDAR-punktmolnsdata av den verifierade ställningen för offsetgenerering. Detta kommer att fungera som bas- eller referensdata.

- **Rutininspektion**: En visuell inspektion varannan vecka utförs normalt av platschefen. På liknande sätt utförs i den föreslagna automatiserade processen rutininspektion och regelbundna skanningar av ställningarna. Flödesschemat i figur 3.1 beskriver den rutinmässiga inspektionsprocessen. Den första skanningen av en verifierad ställning jämförs med rutinmässiga skanningar där det kan ha uppstått förändringar. Om ändringar finns kommer systemet att varna platschefen så att han eller hon kan vidta nödvändiga åtgärder för att säkerställa säkerhet och efterlevnad.

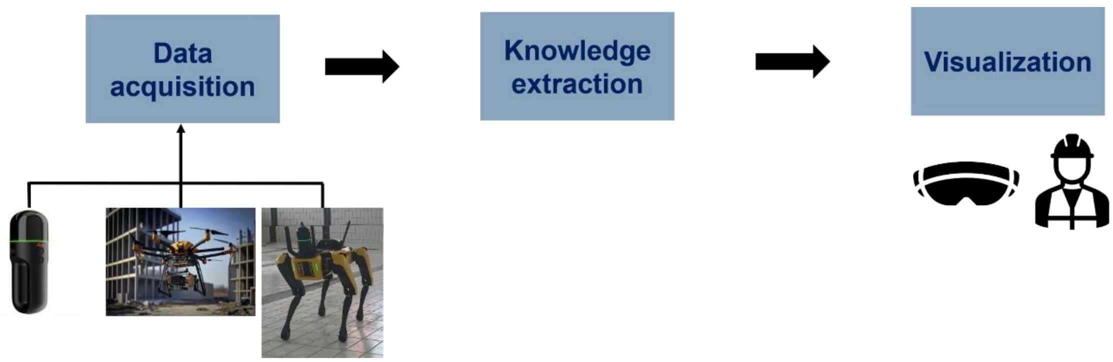



**Figur 3.1 Flöde för rutininspektion**

Den automatiska rutininspektionen omfattar en systematisk utvärderingsprocess,

- *Jämförelse*: Inskannad punktmolnsdata för ställningar vid rutininspektioner jämförs och analyseras med offsetgenereringen för att upptäcka förändringar och avvikelser i ställningens delar.
- *Elementextraktion*: För att kunna identifiera och jämföra enskilda delar av ställningen behöver dessa kunna extraheras. Extraheringen avser delar som stänger, knutpunkter och plana ytor.
- *Kontroll av konstruktionsregler*: Ställningens struktur ska vid varje tidpunkt följa konstruktionsreglerna för att få användas. En verifiering genomförs där den aktuella punktmolnsdatan jämförs mot konstruktionsreglerna som lagts in algoritmerna. Efterlevnaden kan därmed bedömas.
- *Visualisering*: Resultaten presenteras med olika visuella metoder för att skapa tydliga gränssnitt mot platschefen i arbetet med tolkning och beslutsfattande.

Forskningsflödet för automatiserad ställningsinspektion visas i figur 3.2.




**Figur 3.2 Arbetsflöde i forskningen**

### 3.2.1 Datainsamling

Processen börjar med att samla in erforderliga data med hjälp av en LiDAR-enhet, vilken kan vara handhållen, monterad på en drönare eller på ett robotsystem. Enheten samlar in miljontals punktmolnsdata och genererar en detaljerad 3D-representation av en byggnadsställning. Figur 3.3 visar ett exempel på insamlade punktmolnsdata.

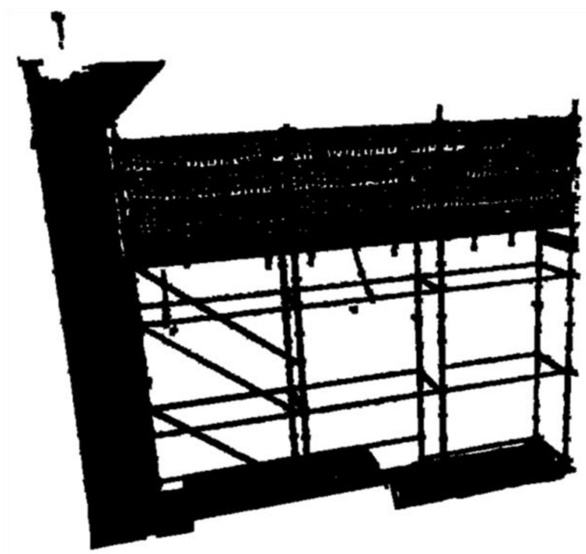
**Figur 3.3 Punktmolnsdata**

### 3.2.2 Informationsbyggande

När punktmolnsdata har samlats in måste de bearbetas för att skapa informationsmängder som kan analyseras. Det är en process i flera steg som beskrivs nedan.

- *Borttagning av extremvärden*: Eliminering av irrelevanta och brusiga datapunkter för att extrahera de objektet som är av intresse.

**(a) ”brusreduktion”**



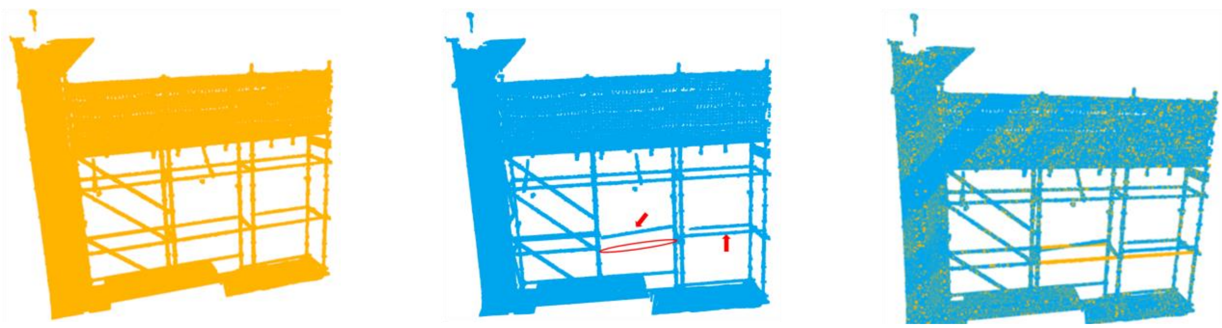
**(b) Offsetgenererad modell**

**Figur 3.4 Process för punktmolnsdata**

- *Nedfiltrering*: För att minska mängden irrelevant data och skapa förutsättning för effektiv bearbetning, utan att förlora viktiga detaljer. Här filtreras väggar bakom och mark under ställningen bort. Figur 3.4 (a) visar väggen och marken i röd färg och Figur 3.4 (b) visar den bearbetade punktmolnsdatan, som i denna rapport kallas offsetgenerering.

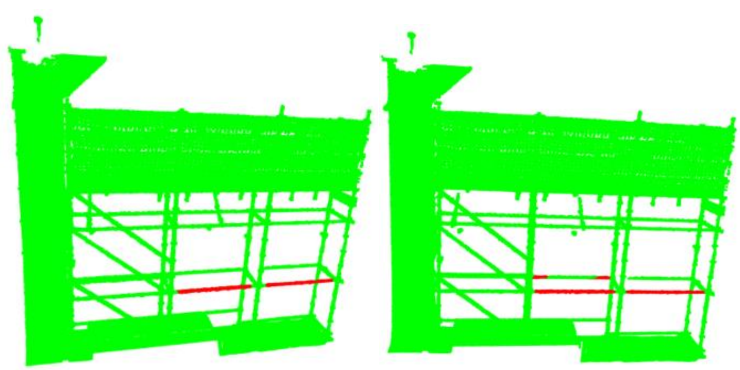
Den bearbetade punktmolnsdatan analyseras sedan med hjälp av AI-algoritmer för:

- *Strukturell jämförelse*: Offsetskanningen jämförs med de löpande ställningsskanningarna för att upptäcka ändringar, saknade eller avvikande delar. Här används metoden med en ”iterativ närmaste punkt” (ICP) -algoritm för att genomföra jämförelsen. Offsetskanningen, den modifierade skanningen och den strukturella jämförelsen visas i figur 3.5.



**Figur 3.5 Strukturell jämförelse**

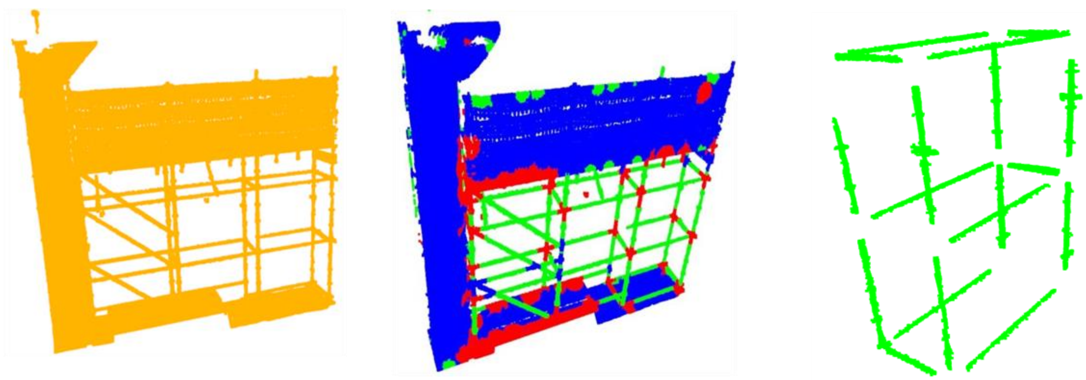
Avstånden i differenserna mellan offestskanningen och den aktuella skanningen beräknas, och jämförs mot ett tröskelvärde för att avgöra om avvikelsen är betydande. I figur 3.6 markeras i rött de områden där avståndet överskrider tröskelvärdet.



**Figur 3.6 Avståndsjämförelse**

Tröskelvärdet är anpassningsbart och kan ställas in av platschefen utifrån bedömda toleranskrav.

- *Elementextraktion*: Med hjälp av klustringsteknik och formigenkänning identifieras och klassificeras de enskilda elementen som stänger, knutpunkter, plana ytor och säkerhetsavstånd. Den bearbetade punktmolnsdatan klassificeras i tre grundläggande former: linjär, plan och sfärisk. Dessa former representerar elementen i ställningar, såsom stång (grön), säkerhetsavstånd (blå) respektive knutpunkter (röd). Den bearbetade punktmolnsdatan för ställningar och extraktion av enskilda element visas i figur 3.7.



**Figur 3.7 Elementextraktion från bearbetad punktmolnsdata**

När elementen har extraherats tillämpas olika typer av klustringsalgoritmer för att gruppera enskilda stänger och för att gruppera knutpunkter.

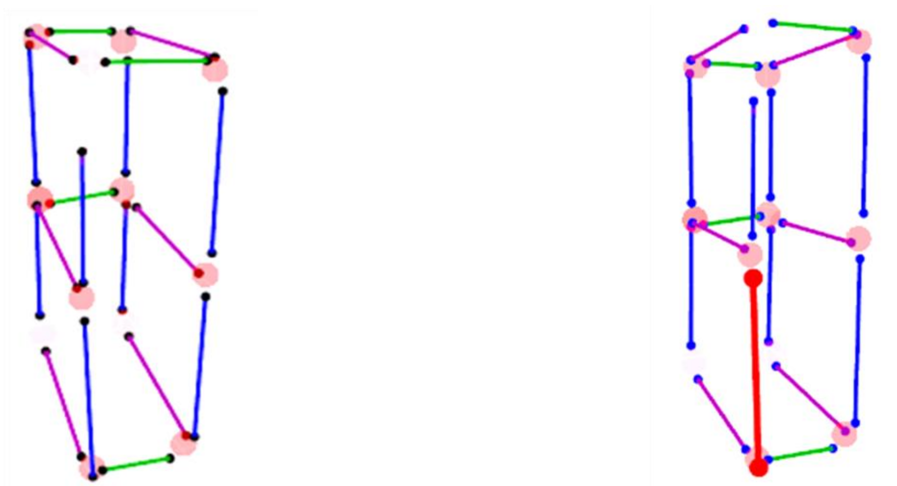
Figur 3.8 visar klustringen av stänger i enskilda element. För att förbättra beräknings-effektiviteten och för enklare representation används en grafdatastruktur för att representera en byggnadsställning. I diagramdatastrukturen representerar kanterna stängerna och noderna motsvarar knutpunkterna i en ställning. De två punkter som är längst bot från varandra i varje kluster representerar ändpunkterna för varje stång som identifierats.

Alla närliggande punkter till ändpunkterna identifieras sedan, och deras medelvärde representerar stavens skärningspunkt eller en led. Grafrepresentationen ger en tydlig och effektiv modell av ställningens struktur, vilket underlättar jämförelsen. Denna grafrepresentation används sedan för att jämföra grafen för den aktuella skanningen med den offsetgenererade. Varje ändring detekteras som förändringar i diagrammets struktur, vilken markeras med röd färg enligt figur 3.9. Detta ger platscheferna visuella varningar om eventuella ändringar, och bidrar till beslutsunderlag för åtgärd.

**Figur 3.8 Klustring av stänger i byggnadsställningen**

### 3.2.3 Visualisering

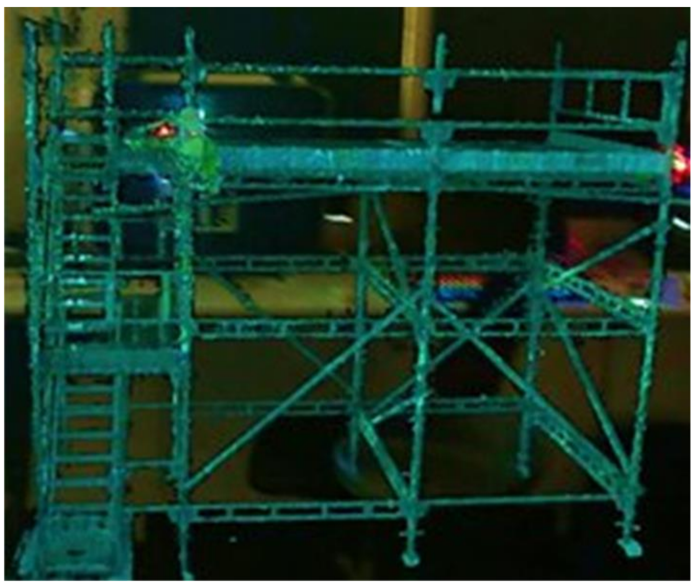
De extraherade delarna av ställningen visualiseras med hjälp av immersiv teknik som Virtual Reality (VR) och Augmented Reality (AR). Detta möjliggör för platschefen att visa 3D-modeller av ställningar och analysera avvikelser i realtid. AR överlagrar den digitala modellen av ställningarna på den verkliga miljön.



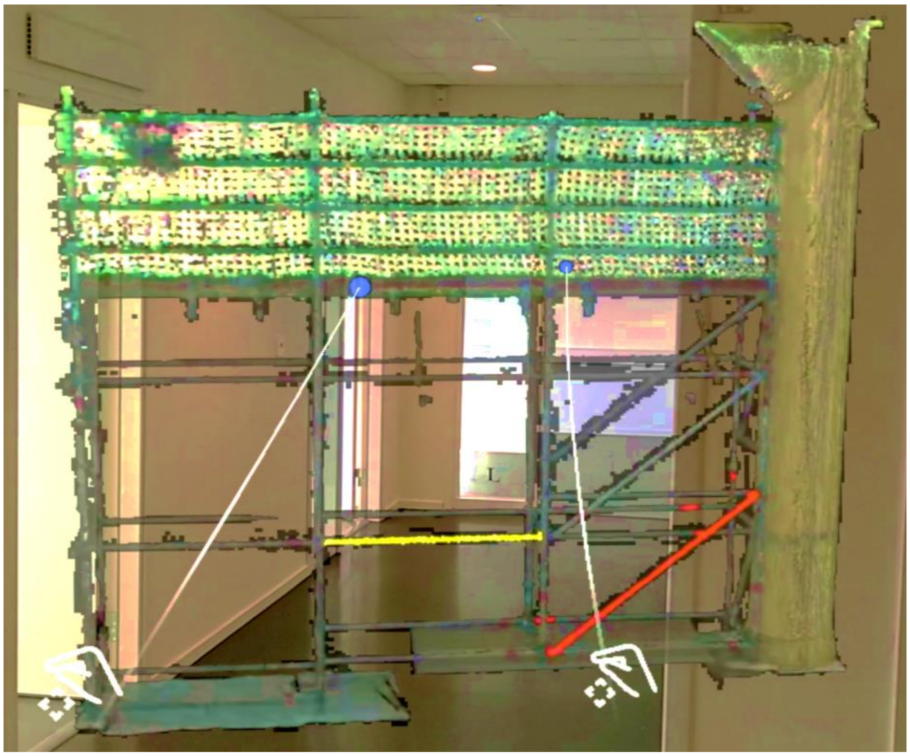
**Figur 3.9 Grafdatastrukturens representation**

Visualiseringen ger platschefer ett intuitivt sätt att identifiera avvikelser. Med VR erbjuds en 3D-miljö där platschefer kan utforska byggnadsställningar från olika vinklar. Dessa tekniker gör det möjligt att få tillgång till och visualisera samma digitala modell från olika platser, vilket också kan underlätta samarbete på distans om sådant behov uppstår. Figur 3.10 och figur 3.11 visar bilder av ställningar genom AR-glasögon, där gula markörer representerar avvikande element och röda markörer representerar saknade delar av ställningen.

Visualiseringstekniker kan stötta och förbättra beslutsfattande genom att tillhandahålla korrekt information i ett överskådligt gränssnitt vilket möjliggör identifiering av säkerhetsrisker. Integrering av AR och VR vid ställningsinspektioner bidrar till säkrare och mer kostnadseffektiva projekt. Verktygen kan också underlätta utbildning i säkerhetsfrågor kopplat till byggnadsställningar. De möjliggör även samarbete på distans vilket ibland kan underlätta inspektionerna. VR och AR har dock, liksom annan teknik, en inlärningskurva där användaren behöver lära sig att hantera de nya verktygen och kunna navigera i modellerna.



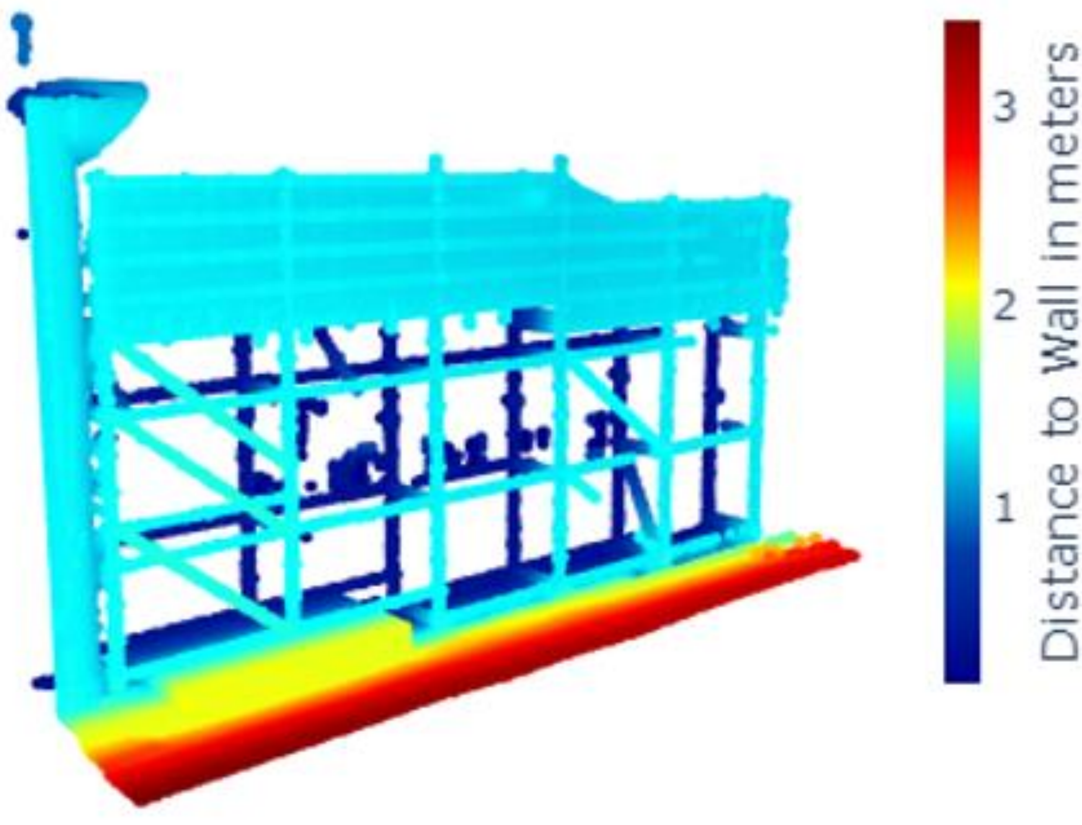
**Figur 3.10 Vy av byggnadsställning genom AR-glasögon**



**Figur 3.11 Vy av byggnadsställning genom AR-glasögon**

## 3.3 Kontroll av konstruktionsregler

De konstruktionsregler som används vid montering av ställningen ska kunna verifieras kontinuerligt så att dessa följs under hela användningen. En av de kritiska kontrollerna är avståndet mellan ställningen och väggen som inte får överstiga 30 cm. Det innebär vissa utmaningar att verifiera automatiskt exempelvis när väggytan är böjd. En annan kritisk kontroll handlar om skyddsräckessystemen där

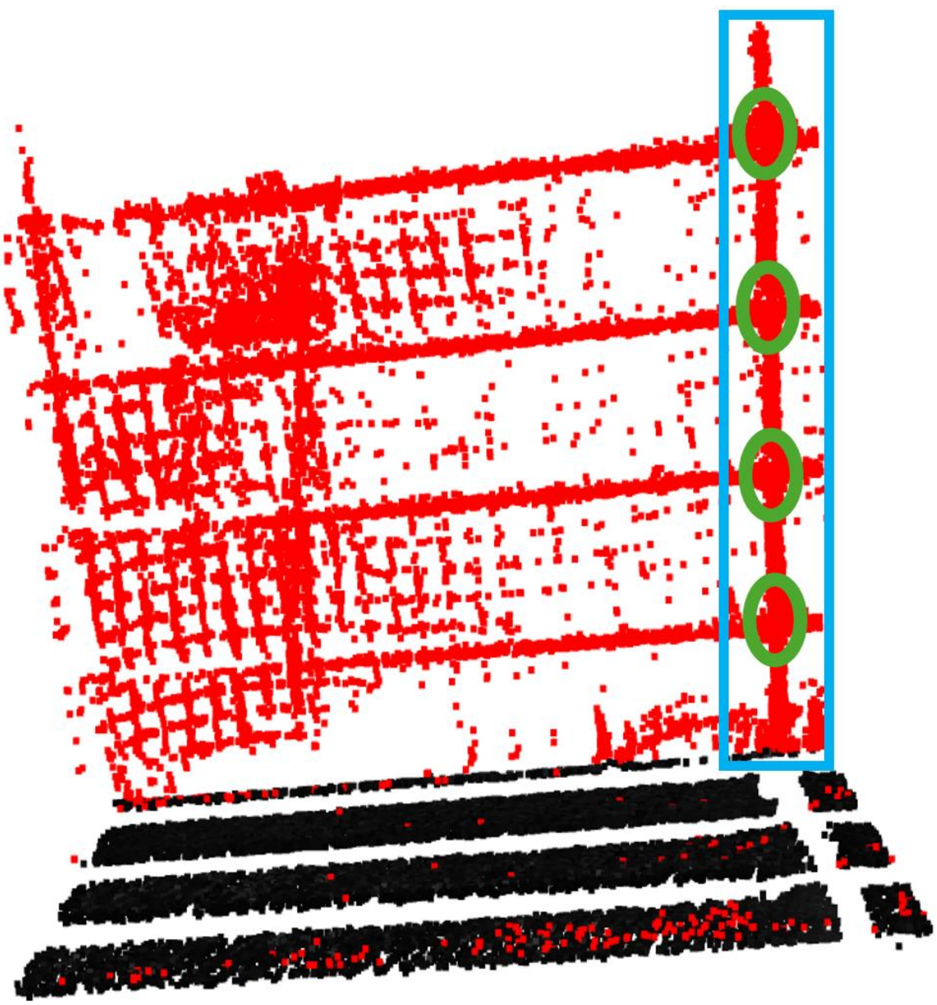



**Figur 3.12 Konstruktionsregel 1**

avståndet mellan stängerna behöver uppfylla vissa krav. Genom automatisk kontroll förbättras möjligheten att efterleva kraven vid varje tidpunkt och det minskar också risken för mänskliga fel vid inspektioner.

Med hjälp av punktmolnsdata och algoritmer som RANSAC identifieras väggen som en plan yta och avståndet mellan ytan och varje ställningspunkt beräknas. I figur 3.12 visas visualiseringen med en färggradient som indikerar närhet till väggen. Röd färg indikerar avstånd som är nära gränsen och blå indikerar ett säkert avstånd som är mindre än 30 cm.

När även kontrollen för konstruktionsregeln för det avancerade skyddsräckessystemet införs extraheras arbetsplattformen från punktmolnsdata. För att identifiera skyddsräcket fokuseras på alla punkter som ligger ovanför arbetsplattformen där skyddsräcken är installerade. En klustringsalgoritm används för att gruppera relevanta punkter samtidigt som mindre punkter (brus) tas bort. Infästningspunkterna där



**Figur 3.13 Konstruktionsregel 2**

skyddsräckena är anslutna identifieras sedan, vilket visas i figur 3.13. Avståndet mellan dessa anger avståndet mellan skyddsräckena och jämförs med reglerna för att bekräfta att de uppfylls. Ett expertsystem skulle också kunna integreras för att ge felmeddelanden i realtid som stöd till beslutsfattande.

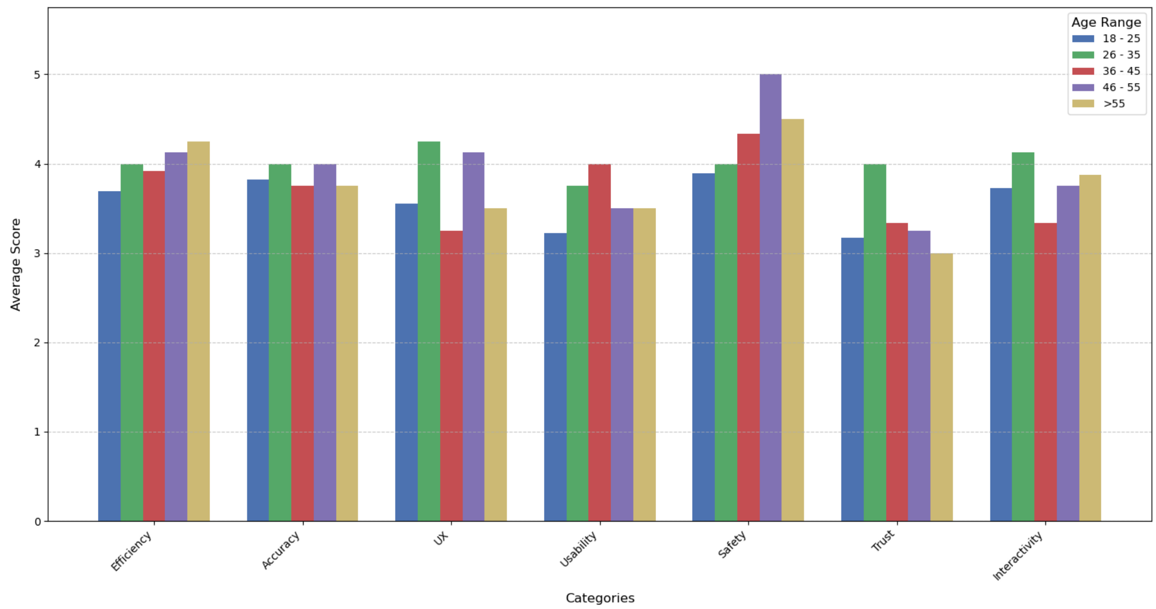
Genom att automatisera inspektionen av ställningar med hjälp av AI kan mänskliga fel minimeras, vilket förbättrar säkerhetsbedömningen och förmågan att säkerställa att konstruktionsreglerna följs. Detta tillvägagångssätt hjälper platschefen att fatta beslut, förbättra säkerheten och öka den operativa effektiviteten på byggarbetsplatsen.

## 3.4 Utvecklat AI-baserat beslutsstöd för inspektionen och analys av byggnadsställningar

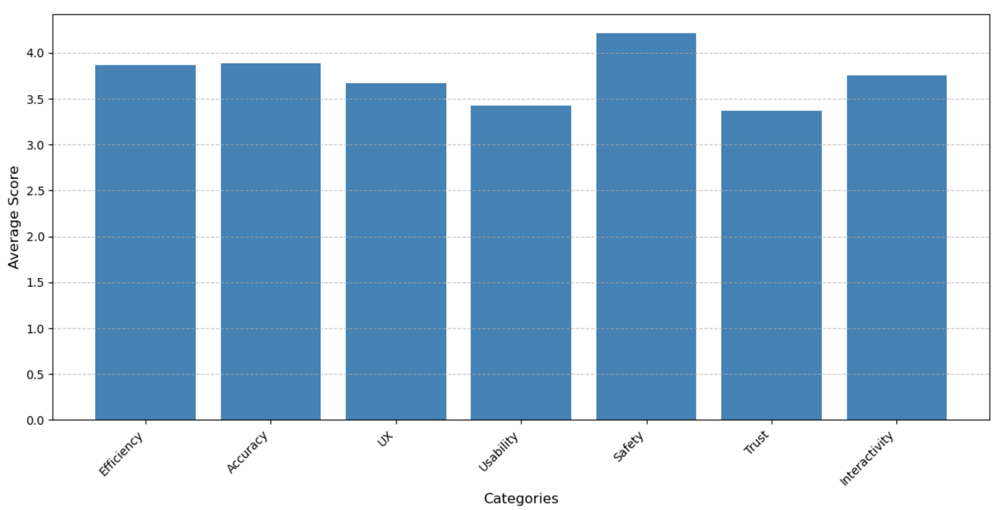
### 3.4.1 Intervjustudie 1 – Användarvänlighet

Integreringen av AI i byggbranschen har potential att omvandla beslutsprocessen under produktionsfasen, vilket kan påverka projektresultaten på ett positivt sätt. AI-baserat beslutsstöd kan förbättra effektiviteten, säkerheten och användbarheten inom byggledning. Flera faktorer, såsom effektivitet, förtroende, användbarhet och interaktivitet, påverkar AI-användningen inom byggbranschen. Den utvecklade lösningen demonstrerar AI-drivet beslutsstöd för platschefer och utvärderar slutanvändarnas uppfattningar. Insikterna samlades in genom enkäter och semistrukturerade intervjuer med platschefer samt andra byggproffs. Analysen bygger på svar från en grupp på 20 deltagare, alla verksamma inom byggbranschen. De insamlade svaren analyserades för att identifiera utmaningar och användarnas förväntningar avseende AI-användning inom byggsektorn.

Stapeldiagrammet i Figur 3.14 presenterar genomsnittliga poäng i olika kategorier, såsom effektivitet, noggrannhet, användarvänlighet, säkerhet och förtroende, segmenterade efter olika åldersgrupper. Genom analysen framkom att säkerheten var den högsta prioriteten, vilket förstärker vikten av AI-verktyg för att säkerställa stabilitet på ställningar och minska riskerna på arbetsplatsen. Detta återspeglas i Figur 3.15.

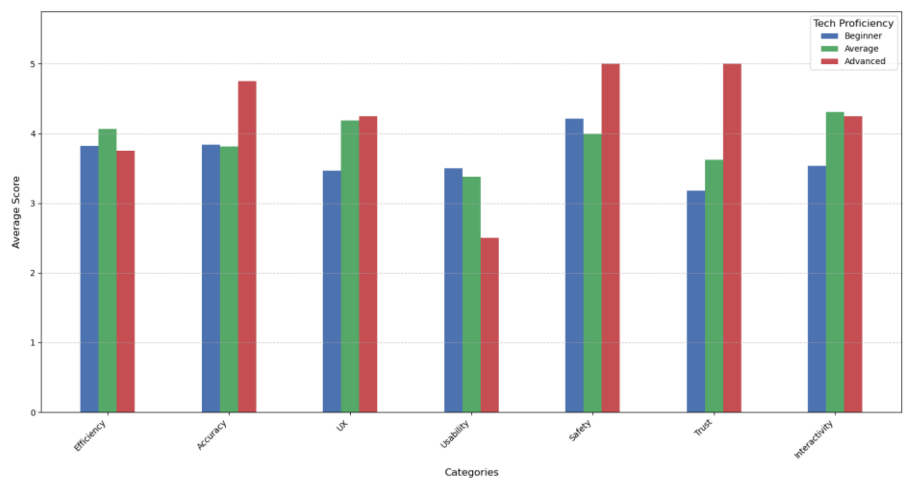



**Figur 3.14 Key factor score by age group**




**Figur 3.15 Key factor mean score**

AI-lösningar bör också vara intuitiva och sömlöst integrerade i det befintliga arbetsflödet. Genom att integrera utformningen av AI-verktyg med användarupplevelsen i åtanke kan beslutsfattandet bli mer tillförlitligt, transparent, spårbart och effektivt. Beroende på kompetensnivå segmenteras kategorierna enligt Figur 3.16. De statistiska verktyg som används för att analysera svaren är skalbara och kan vid behov tillämpas på en större grupp deltagare om det skulle behövas i framtiden.




**Figur 3.16 Key factor score by proficiency**

### 3.4.2 Intervjustudie 2 – Användbarhet och pålitlighet

En kvalitativ studie har inom projektet genomförts (*Simu K. och Samuelson O., 2025*) med representanter från de två entreprenadföretagen som medverkat i projektet. Två forskningsfrågor (FF) ställdes upp för den delstudien:

> *FF 1: Hur kan AI stödja beslutsfattande för byggarbetsplatsledning, angående pålitlighet, användbarhet och begränsningar för beslutsfattande?*

”Begränsningar för beslutsfattande” har delats upp efter Daft et al. (1986) i: tillgång till informations-mängder, kognitiv analysförmåga samt begränsningar i tid.

> *FF2: Vilka heuristiska fördomar kommer att vara möjliga att hantera och reducera genom AI?*

Respondenterna i studien utgjordes av fem personer: tre platschefer, en produktionschef och en projektingenjör. En platschef var anställd på ett SMF-företag och övriga på ett stort företag.

Studien utgick från ett teoretiskt ramverk baserat dels på teorier om rationellt beslutsfattande (Daft, 1986) där informationsinsamling och analys av information är centrala. I verkligheten är dock sällan beslutsfattande så linjärt och rationellt, utan begränsas av till exempel kognitiva förmågor att processa information, tidsbegränsningar i att samla in och analysera samt inte minst mänskligt beteende som innebär förenklingar och ”fördomar” baserade på tidigare erfarenheter och kunskaper (Tversky et al., 1974; March, 1994).

Studien har genomförts med en kvalitativ ansats och i fyra steg. **Steg 1** innefattade att tillgängliggöra prototypen till verktyget som beskrivs i kapitel 3.2 ovan. Verktyget syftar till att kunna jämföra byggnadsställningars status vid olika tidpunkter och därmed identifiera möjliga fel. Detta möjliggörs genom att använda Lidarskanning som skapar en digital modell av den aktuella ställningen, samt flera utvecklade algoritmer som identifierar delar och knutpunkter i modellen. I **steg 2** genomfördes en demonstration för respondenterna där dels fick en presentation av verktyget, dels fick möjlighet att själva testa att navigera och röra sig i modellen för att bedöma potentialen i verktyget. Som **steg 3** genomfördes semistrukturerade intervjuer med de fem respondenterna var för sig. Intervjuerna täckte de tre områdena 1) insamling av information rörande status av byggnadsställningar, 2) analysering av insamlad information samt 3) beslutsstöd för att vidta åtgärder. De tre områdena betraktades både från perspektivet hur detta går till idag, och perspektivet hur det skulle fungera med det beskrivna och demonstrerade verktyget. Även respondenternas förväntningar på framtida AI-tillämpningar lyftes fram.

Resultatet av studien sammanfattas i tabell 3.1 som beskriver respondenternas befintliga arbetssätt liksom deras uppfattningar och förväntningar på ett AI-stött beslutsstöd enligt demonstrationen.

**Tabell 3.1 Sammanfattning av respondenters uppfattning av befintligt respektive automatiserat arbetsflöde**

| *Befintligt arbetsflöde* | *Beskrivna förväntningar på AI-stött beslutsfattande* |
|---|---|
| **Insamling av information om ställningens status** | |
| Visuell inspektion av platschefen, mer eller mindre regelbundet. | Regelbunden insamling av information med hjälp av skanningsverktyg |
| Fokus på kritiska punkter utifrån tidigare erfarenhet och kunskap | Noggrann information om avvikelser samlas in oavsett var de förekommer |
| Tillit i rapporter och från individer på arbetsplatsen rörande avvikelser från det normala | Regelbunden skanning med information om avvikelser |
| Tidskrävande att genomföra för individer, särskilt vid stora och komplexa ställningar. | Möjligt att genomföra när som helst med avsevärt mindre tidsåtgång för manuellt arbete. |
| **Analys av information** | |
| Kräver kunskap om konstruktionsregler för byggnadsställningar för att kunna bekräfta status på ställningar och upptäcka avvikelser | Användning av designregler för varje befintlig ställning för att upptäcka avvikelser. |
| Tillgänglig information är begränsad till det som samlas in vid visuell inspektion, baserat på vad varje individ kan ta till sig och förhålla sig till, för att upptäcka avvikelser. | Kvittera avvikelser i relation till originalmonterade ställningar som är certifierade som OK. |

| **Beslutsstöd** | |
| --- | --- |
| Behov av att kunna förlita sig på underleverantörer samt egen förmåga att bekräfta en säker ställning. | Nyttjas som stöd för beslut men inte för att fatta beslut. |
| | Verktyget behöver bevisa sin pålitlighet upprepade gånger innan tillförlitlighet kan uppstå. |

Studiens slutsatser har formulerats enligt nedan, kopplat till respektive forskningsfråga.

*FF 1: Hur kan AI stödja beslutsfattande för byggarbetsplatsledning, angående pålitlighet, användbarhet och begränsningar för beslutsfattande?*

För att kunna lita på ett AI-verktyg för löpande beslutsstöd måste det konsekvent ge korrekta svar som överensstämmer med individuell erfarenhet och kunskap. Respondenterna är tydliga med att beslutsansvaret inte kommer att delegeras till ett AI, men de är positiva till det stöd digitalisering och AI kan ge. Begränsningar som upplevs i nuvarande beslutsfattande skulle enligt respondenterna kunna minska med hjälp av AI, vilket skulle innebära att platschefer sparar tid och får korrekt information. AI kan systematiskt samla, bygga och dela erfarenheter, vilket ger ett mer tillförlitligt beslutsunderlag jämfört med checklistor och individuell kunskap.

*FF2: Vilka heuristiska fördomar kommer att vara möjliga att hantera och reducera genom AI?*

Heuristiska fördomar används, ofta omedvetet, för att underlätta snabbare och enklare beslutsfattande av människor. Våra resultat tyder på att det är möjligt att hantera och minska flera heuristiska fördomar i det rationella beslutsfattandet. Med stöd av AI kan en större mängd information samlas in och analyseras, och därmed adressera tidsbegränsningarna. Detta skulle minska behovet av genvägar och beroendet av "magkänsla" och tidigare erfarenheter.

## 3.5 Slutsatser

Projektet har undersökt ett flertal användarfall där digitalisering med AI-stöd skulle kunna bidra till ett effektivare och mer informerat beslutsfattande för platschefer på en byggarbetsplats. Potentialen för detta bedöms vara hög. Ett av de identifierade fallen, byggnadsställningar, har studerats djupare och där har en prototyp utvecklats som också testats och utvärderat av representanter för platsledningen hos två företag. Följande konkreta slutsatser kan dras utifrån den fördjupade fallstudien:

- *Förbättrad säkerhet och efterlevnad*: Med hjälp av teknik som AI och LiDAR kan inspektioner av ställningar göras automatiskt, vilket minskar risken för mänskliga fel och förbättrar efterlevnaden av säkerhetsföreskrifter.

- *Effektivare inspektioner*: Traditionell manuell inspektion är tidskrävande och ger utrymme för mänskliga fel och ”confirmation bias”, dvs risken att endast hitta fel baserat på egen erfarenhet. AI-baserade inspektioner ger förutsättning för mer frekvent övervakning av ställningar.
- *Ökad förmåga till informerat beslutsfattande*: Tekniken kan stötta platschefens förmåga att hämta in information, analysera och tolka förändringar hos byggnadsställningar. Detta ökar förmågan att fatta välgrundade beslut. Det är också tydligt från studien att förtroendet för tekniken behöver byggas upp över tid, och att beslut fattas av människor, men med stöd av tekniken.
- *Skalbarhet*: Det AI-baserade systemet kan anpassas i skala för att kunna hantera olika typer av byggarbetsplatser med byggnadsställningar i olika storlekar och komplexitet.
- *Förbättrad operativ effektivitet*: Automatiska rutininspektioner kan minska arbetsbelastningen för platschefer, och frigöra tid för andra kritiska uppgifter.

Projektet har också gett insikter om hur en fortsatt utveckling kan bidra till ytterligare nytta inom stöd för beslutsfattande. Fortsatt forskning inom området kan bidra till:

- *Framtida integration*: AI-baserade system kan förbättras ytterligare med expertsystem som integrerar verifiering av konstruktionsregler med hjälp av fördefinierade säkerhetsstandarder. Sådan integreringen kan leda till normativ analys där AI både kan upptäcka regelöverträdelser eller avvikelser och föreslå korrigerande åtgärder.
- *Avancerade AI-algoritmer*: Tekniker för djupinlärning kan utforskas och nyttjas för att ytterligare förbättra inspektion av ställningar med större noggrannhet och anpassningsförmåga.
- Integrering av data för holistisk platshantering: AI-systemet kan utökas för att införliva och integrera annan data från byggarbetsplatsen, rörande tex. tid- och resursplaner, materialleveranser och progression på arbetsplatsen. Detta kan ge en mer heltäckande bild och övervakningen av hur byggprojektet fortskrider. För att ett AI-system ska kunna bidra med optimering är tillgången till aktuella och korrekta data en viktig förutsättning.

**Tabell 3.2 Projektets förväntade respektive uppnådda resultat**

| Förväntningar | Vad som uppnåtts |
|---|---|
| En behovskarta baserad på platsledningens behov | **Detaljerad identifiering av behoven under produktionsfasen ur en platschefs perspektiv**<br>• Behov identifierade genom intervjuer och platsbesök.<br>• Behoven sammanställda och i form av användningsfall såsom armeringsstål, byggnadsställningar, erfarenhetsåterföring, hälsa och säkert samt optimerad planering.<br>• Genomförbarhetsstudie för att identifiera det mest prioriterade användningsfallet och möjliga tekniker för att stötta platschefen. |
| En teknikplattform för beslutsstöd i produktionsfasen | **Plattform baserad på AI och digital teknik till stöd för platschefen i daglig planering och implementering**<br>• Utvecklat en teknisk plattform med hjälp av molnet (AI Factory) och AI-analyser av LiDAR-data.<br>• Integrerad visualiseringsteknik som AR/VR för intuitiv användarinteraktion.<br>• AI-driven övervakning och regelkontroll av byggnadsställningar för att stötta beslutsfattande. |
| En demonstrator baserad på digital modell | **Demonstrator för att verifiera de utvecklade komponenterna med hjälp av en digital modell, skräddarsydd för beslutsprocessen**<br>Punktmolnsdata och AI har använts för generering av digitala modeller för ställningar vilka stöttar:<br>• Utveckling av metodik för att utvärdera överensstämmelse med konstruktionsregler genom generering av digital representation av ställningar från punktmolnsdata.<br>• Utveckling av algoritmer för att automatisera inspektionsprocessen och upptäcka förändringar i ställningen över tid.<br>• Varningar och beslutsstöd med hjälp av AR/VR-immersiv teknik och samarbete på distans. |

| | |
|---|---|
| En guide för digitalisering och AI i produktionsfasen | **Guide för intressenter i utvärdering och implementera av digital teknik och AI som bidrar till att öka effektiviteten i produktionsfasen av ett byggprojekt**<br>Detta projekt presenterar en fallstudie för digitalisering av temporära strukturer (byggnadsställningar). Ytterligare tillämpning av AI-baserade verktyg och visualiseringar har demonstrerats. |

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# Bilagor

## Bilaga 1 – A conceptual model for AI-enabled digitalization of construction site management decision making

En konceptuell modell för AI-baserad digitalisering av beslutsfattande inom byggarbetsplatshantering. Publicerad vid Internationell kongress och workshop om industriell AI och eMaintenance, Luleå 2023.
*Sharma G., Karim R., Simu K. och Samuelson O. (2023)*

## Bilaga 2 – Industrial AI for Safety on Construction Site

Industriell AI för säkerhet på byggarbetsplatsen. Lämnade in och presenterade ett utökat abstrakt i Artificial Intelligence in Architecture, Engineering and Construction, 2024, Helsingfors.

## Bilaga 3 - AI for enhanced Site Management: Integrating AI Decision Support for Scaffolding Inspection

Whitepaper om AI för förbättrad platshantering: Integrera AI-beslutsstöd för inspektion av ställningar.

*Prabhu, S. Patwardhan, A. och Karim, R. (2024)*

## Bilaga 4 – AI as support for daily decisions at construction sites

AI som stöd för dagligt beslutsfattande kring ställningar på byggarbetsplatser. Insänt i Internationell kongress och workshop om industriell AI och eMaintenance, Luleå 2025.
*Simu K. och Samuelson O. (2025)*

## Bilaga 5 - Enhancing Decision Support in Construction through Industrial AI

Förbättra beslutsstödet i byggbranschen med hjälp av industriell AI. Insänt i Internationell kongress och workshop om industriell AI och eMaintenance, Luleå 2025.

*Khanna, P., Prabhu, S. Karim, R. och Tretten, P. (2025)*

## Bilaga 6 - POINT CLOUD BASED MONITORING OF SCAFFOLDING: ASSISTANCE TO SITE MANAGER DECISIONS

Punktmolnsbaserad övervakning av ställningar: stöd vid beslut av platschefen. Inlämnad/Under granskning.

*Prabhu, S. Patwardhan, A. och Karim, R. (2025)*

# A Conceptual Model for AI-Enabled Digitalization of Construction Site Management Decision Making

**Gaurav Sharma, Ramin Karim, Olle Samuelson, and Kajsa Simu**

**Abstract** Artificial Intelligence (AI) and digitalization are changing the landscape of performing projects in the construction industry. In construction projects, the responsibility for achieving the required scope within a specified timeframe and estimated cost lies with the project managers. To meet these stringent requirements, site managers must make on-site project decisions, relying heavily on their past experiences and intuition. Moreover, the complexity of the decision-making process is amplified by the need to manually review various information sources such as Building Information Modelling (BIM), Bill of Quantities (BOQ), construction drawings etc. The heterogeneity, complexity, availability, accessibility, and volume of these contents that need to be processed by the decision-maker pose risks to the decision-making processes that may adversely impact resource consumption, planned time, and cost. The emerging technologies related to AI and digitalization are expected to improve the effectiveness and efficiency of the decision-making process in construction projects. However, the development and implementation of such technologies are highly dependent on the identification and definition of contexts to which AI and digital technologies add additional value. Hence, the purpose of this research paper is to study and explore the decision-making process of site managers. This paper also provides the identified gaps and potential of utilizing AI and digital technologies to assist in decision-making. Further, this paper proposes a set of conceptual models that combine hardware and AI algorithms to support the site decision-making process. The findings provide insights into the complexities site managers face and offer innovative approaches to mitigate risks and improve decision making efficiency.

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**Keywords** Construction management · Construction site decision-making · AI-based decision support tools · AI Factory · Asset management

## 1 Introduction

Digitization has rapidly transformed the construction industry by enhancing efficiency, streamlining processes, and improving project outcomes. Artificial Intelligence (AI) is emerging as a transformative tool in the construction industry. It has the potential to enable new era of digitalization of site management processes to optimise operations, reduce reworks and failures, ensure safety and security at the construction site, and harmonise the workflows. The potential of AI can be enhanced when combined with hardware platforms such as LiDAR, Metaverse, AR, VR, etc. [1]. Also, appropriate data analytic techniques are required to fit the data and generated information for AI. These technologies can facilitate numerous iterations through tracking and visualising construction progress and running algorithms to detect compliance with design.

Additionally, AI can offer diverse applications in scheduling and procurement, predicting cost overruns by analysing factors like project size, contract type, and managerial competence. It can also aid in risk management by prioritising issues and collaborating with high-risk subcontractors. AI optimises work cycles, improving efficiency and reducing delays.

Above all, AI can equip them with advanced tools to enhance quick and informed decision-making for Site managers [2]. These managers, play a crucial role in overseeing operations, managing resources, and ensuring timely project completion. They are signing authority for project-related issues and are under pressure to make quick decisions which can alter the course of the project [3].

However, there are research gaps in leveraging AI solutions empowered by digital technologies effectively and efficiently in the construction industry. Despite some progress, there are unexplored research areas in leveraging AI solutions as a decision-support tool in the construction industry, some of these contributions and initiatives are highlighted by Pan and Zhang Exploring this untapped potential and addressing the above-mentioned challenges can shape the industry's future [4]. Based on the above premises, the aim of this paper is twofold: firstly, to explore the issues and challenges that site managers face in their day-to-day decision-making, and secondly, to suggest conceptual models for developing a decision support toolkit using digitalization and AI-based tools.

## 2 State of the Art

Globally, individuals and businesses spend over $10 trillion per year on construction-related activities—and that's projected to keep growing by 4.2% until 2023. Part of this enormous amount of spending is on, and enabled by, rapidly moving technological advancements that touch all areas of the ecosystem. The potential applications of machine learning and AI in construction are vast. Requests for information, open issues, and change orders are standard in the industry. Machine Learning (ML) and Deep Learning (DL) technologies are like smart assistants that can search among this vast amount of data and provide conclusions to the decision-makers [5].

The development of the construction industry is severely limited by the complex challenges it faces such as cost and time overruns, health and safety, productivity, and unavailability of labour. Also, the construction industry is one the least digitalized industries in the world, which has made it difficult for it to tackle the problems it currently faces [2]. An advanced digital technology, Artificial Intelligence (AI), is currently revolutionising industries such as manufacturing, retail, and telecommunications. The subfields of AI such as machine learning, knowledge-based systems, computer vision, robotics and optimisation have successfully been applied in other industries to achieve increased profitability, efficiency, safety, and security [2]. While acknowledging the benefits of AI applications, numerous challenges exist in use of AI in the construction industry [2]. For example: Life safety is an area where companies prefer to choose the conventional path and hesitate when it comes to adapting technologies such as artificial intelligence, as it is often equated with leaving an individual's life in the hands of artificial intelligence [5].

Site decision-making plays a vital role in the management of construction sites, as managers are tasked with overseeing multiple activities to ensure project success. This overview investigates the situation faced by construction site managers, examines the characteristics and statistics related to decision-making, and explores the prospects of digital technologies/AI on the decision-making process. This section draws insights from various research papers, thus, providing a basis for the discussions in subsequent sessions.

### *2.1 Construction Site Managers*

Amid the dynamic construction sites, the site/construction manager is responsible for handling countless challenges, staying determined to finish the project within a given time frame and cost, at the same time adhering to the quality. Site managers generally experience being stuck in between production objectives and day-to-day administrative/decision routines [6]. The site managers witness high level of anxiety irrespective of their grade. They are stressed because of role insecurity emanating from, fear of failure, committing mistakes, work overload, physical working conditions etc., [3]. Furthermore, construction managers are under Constant time pressure, which turns out to be the highest source of stress [3]. Decisions made by site managers play a key role in adhering to the time schedule, as wrong decisions can lead to rework, injury, or erroneous estimates, leading to time overruns. Thus, there is a need for a decision support tool to ease the life of construction site managers.

### 2.2 Decision-Making on Construction Site

As we discussed above, construction site managers make important decisions to manage various aspects of construction projects. Their goal is to ensure that work packages run smoothly, and the project is completed successfully. Construction site managers primarily focus on making critical decisions related to technical and engineering aspects, accounting for approximately 65% of their responsibilities. In addition, finance-related decisions also hold significant importance, constituting around 29% of their job [7].

Construction site managers regularly make decisions, regarding construction methods and techniques, material selection and specification, safety measures and risk mitigation. They also decide on financial aspects such as project scheduling, vendor selection etc.

At construction sites, decision-making is a dynamic process that draws upon the collective experience and knowledge of site personnel. These decisions are informed by a multitude of factors, with a significant emphasis on previous experiences, accounting for approximately 44% of the decision-making process. Furthermore, domain knowledge plays a pivotal role, contributing approximately 26% to the decision-making process. Valuable insights from colleagues also shape decisions, making up around 12% of the process. Additionally, past records and historical data analysis contribute approximately 9%. Additionally, 70% of these decisions had to be taken on the same day [7]. The time pressure on site managers often fosters hasty decision-making. Moreover, site managers must deal with a lot of information overload, which they need to go through to make their decisions [6].

The above discussion highlights a gap where emerging digital technologies can assist construction managers in decision support.

### 2.3 AI and Digitalization as a Decision Support Tool

The foremost digital technology, Artificial intelligence (AI), has helped to achieve significant contributions to the improvement of business operations, service processes and industry productivity in recent years [8]. AI is poised to make a big impact on the way things are done in several industries as an innovative approach to improve productivity and solve challenges. The construction industry faces a productivity problem and other challenges, which has the potential to be solved by AI [2].

The potential applications of machine learning and AI in construction are vast. Requests for information, open issues, and change orders are standard in the industry. Machine Learning (ML) and Deep Learning (DL) technologies are like smart assistants that can search among this vast amount of data and provide conclusions to the decision-makers [9]. AI has the capability to harness data and leverage on the abilities of other technologies to improve construction processes [2].

Thus, the advent of AI and digitization has opened new avenues for construction management. AI has the potential to improve site decision-making processes through automation, data analysis, and predictive modelling [2]. Additionally, digital technologies such as Building Information Modelling (BIM), Construction 4.0, Augmented reality (AR), Virtual reality (VR), LIDAR etc. have enormous potential in enhancing site decision-making capabilities [1].

However, there are still major challenges such as lack of clear benefits, feasibility, data management, technical issues, fragmentation, lack of skilled manpower etc. in realising true potential of digitalization/AI in the construction site management process [10]. One of the approaches to solve many of these challenges is to integrate identified technologies in a single platform and create an ecosystem of technologies that can demonstrate clear benefits [11]. Therefore, there is a need for the construction technology ecosystem to move from point solutions towards integrated technology platforms [12].

Digitalization can provide benefits such as increased internal efficiency in construction management processes and improved insight in the linkage between everyday tasks and the overall goals. Thus, there is a tangible need to demonstrate how the expected benefits can be achieved by deploying new emerging digital technologies [13].

## 3 Research Methodology

This section presents the research methodology used in this paper for identifying issues and challenges in construction site decision making and to suggest conceptual models using which AI can act as a decision support tool. This research is based on 'Qualitative research methods' and we have conducted case study research and deployed techniques such as semi-structured interviews and expert consultations.

The work began with a State-of-the-Art study. This step revealed a gap in the usage of AI and digitalization in the decision-making process from the perspective of site managers. To gather specific insights, we designed a Semi-structured interview using clear and concise questions. We prepared a protocol for on-site discussions to ensure consistency in data collection.

We targeted site managers and supervisors from two case study sites in Luleå, Sweden, who possessed valuable first-hand experience. Semi-structured interview was conducted with them, following the protocol. The results of this stage are described in Sect. 4.1.

We analysed the identified issues and challenges, seeking input from AI and machine learning experts to develop conceptual models for addressing problems in construction decision-making. To ensure practicality, we consulted with construction experts at LTU, validating the relevance and viability of the proposed solutions. This collaborative approach improved the potential effectiveness of the models, aligning them with real-world construction needs. The results of this stage are described in Sect. 4.2. The execution of the research is summarized below in seven steps (also described in the Fig. 1).

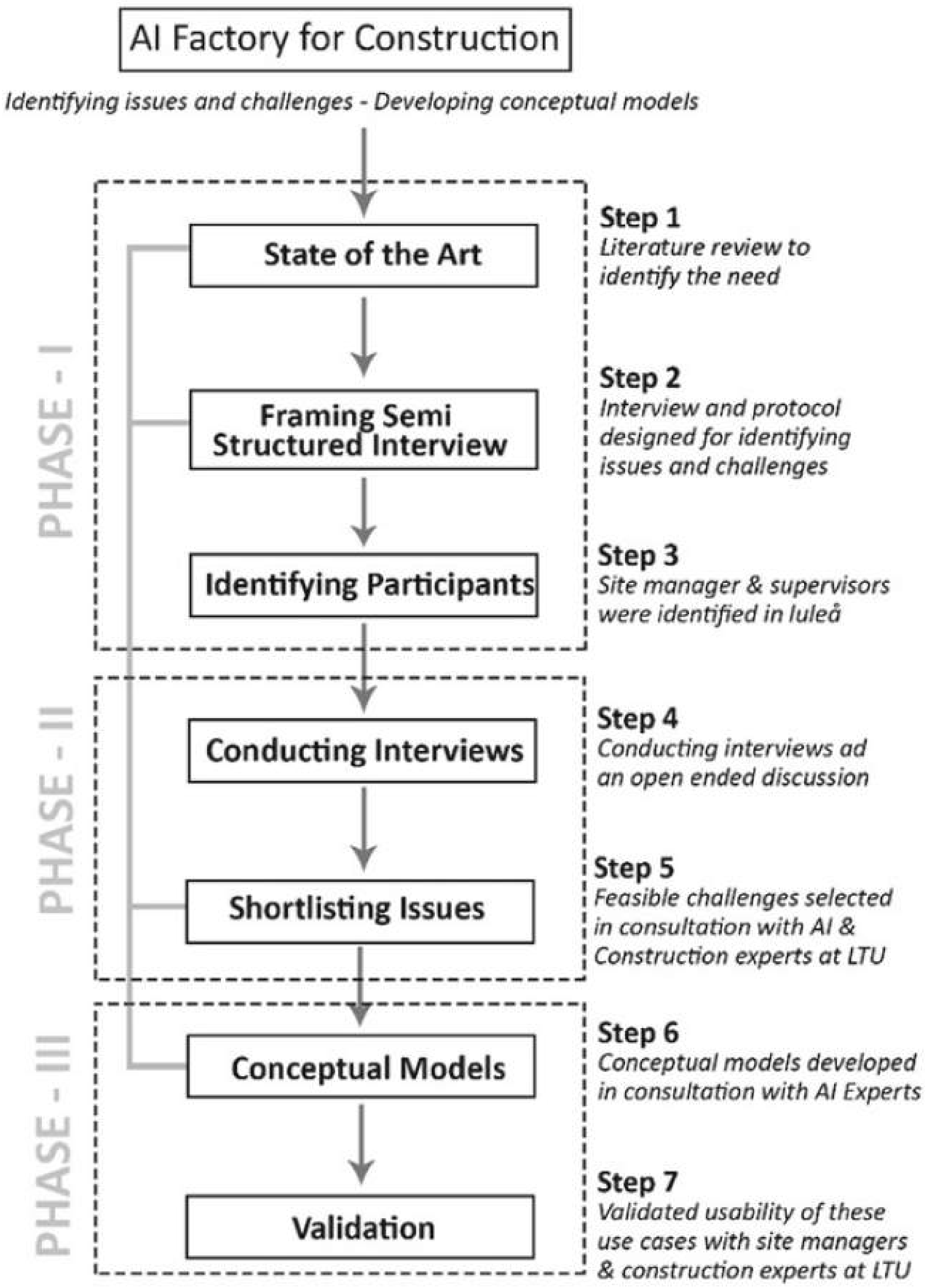



**Fig. 1** Methodology for the proposed work

**Step 1:** *State of the Art study*: this step identifies our research purpose; in this step we also establish the need for AI-based tools in the construction decision-making process. Thus, in this section, we are finding a gap in the decision-making process from the site manager's perspective.

**Step 2:** *Framing Semi-structured interview*: To identify specific issues for the next phase of our project, we conducted semi structured interviews based on questions developed through online study and expert consultation (from LTU). A protocol was also prepared to guide on-site discussions.

**Step 3:** *Identify participants*: We Identified participants who were site managers/ supervisors from our 2 case study sites in Luleå, Sweden. These sites were executed by Tier 1 and Tier 2 sized construction firms.

**Step 4:** *Conducting semi structured interviews*: We conducted an open discussion with site managers and supervisors. Participants were guided through the questions in an open discussion format to encourage maximum information flow from their side.

**Step 5**: *Shortlisting feasible issues and challenges*: We analysed the collected responses by reviewing and identifying common themes and patterns. A preliminary screening was done in consultation with AI experts in our team and construction experts at LTU to do a preliminary shortlisting of issues to take forward. We have chosen challenges which are in line with our AI factory platform in the division of Operations & maintenance division at LTU.

**Step 6:** *Developing Conceptual models*: After discussing the issues with AI and ML experts, conceptual models were developed for feasible problems. *While developing conceptual models we performed minor case studies in other domains within AI factory in operation & maintenance engineering division (LTU), to understand deployment of technologies/AI*.

**Step 7:** *Validation:* After developing potential solution concepts, we discussed them again with site managers and construction experts at LTU to determine their viability and relevance.

## 4 Results and Analysis

The Results section is divided into two parts. Firstly, we present the Results from the semi-structured interviews, where we describe the five challenges identified in construction site decision-making. In the second part, the Analysis section, we present conceptual models after analyzing the challenges in consultation with construction/ AI experts at LTU.

Firstly, when discussing challenges in decision-making, site managers highlighted the verification of executed components compared to the drawings as a major challenge. Another significant concern raised was the safety of personnel involved in various activities. Furthermore, the accessibility and availability of information from past project experiences and company databases were mentioned as additional issues. Additionally, adhering to schedules in terms of time and cost was reported as a challenge by site managers. These challenges are discussed in detail in Sect. 4.1.

Secondly, in the proposed conceptual models, we describe various toolkits tailored to specific use cases. These toolkits integrate different technologies to enhance decision-making for site managers. The technologies include LIDAR scans for documenting as-built structures and developing algorithms to compare scans with design and safety codes. We also propose algorithms for identifying and visualizing deficiencies using virtual or augmented reality environments. AI-based solutions encompass algorithms for processing large datasets and providing natural language responses, predicting attentiveness to address safety challenges, and forecasting cost and time overruns based on historical data. Additionally, one use case incorporates health/location tracking devices as hardware support. Detailed descriptions of these conceptual models are provided in Sect. 4.2.

## *4.1 Identified Issues and Challenges in Decision-Making (Results)*

In this section, we compile a list of identified issues and challenges that have been deemed feasible to be addressed through the implementation of an AI-based construction decision-making support platform (AI factory for construction platform).

### 4.1.1 Reinforcement Steel

- Problem is, once the steel is tied in a concrete member, it is difficult to verify its adherence to the drawings/ BIM model.
- This is especially the case in foundations where the density of steel is high.
- Most important verification criteria to verify, Diameter of reinforcement bars, their numbers, positioning, and lapping length. Application is suitable for Pre-Cast/ In-situ applications.

### 4.1.2 Temporary Support

- Problem is, once the temporary supports are tied, it is difficult to verify its adherence to codes.
- This is an issue with decision making as the site manager is supposed to verify these installations and approve them as 'safe to use'.
- She/He must physically measure for the support distances 'centre to centre', other requirements as per codes and physically sign them that they are safe to use.

- It is difficult to measure and verify on site.

#### 4.1.3 Lesson Learned

- Problem is, we usually lose all the experiences from previous projects as the teams are dismantled and reorganized.
- A lesson learned session is always conducted and the data is captured is a pre-defined format.
- This data is then stored in project servers which are often inaccessible for the new project teams.
- Even if the files are accessible for everyone, it is time consuming to navigate through a lot of data and reach your point of interest.

#### 4.1.4 Accidents and Health Tracking

- Problem is that people often keep wandering in areas which are hazardous to operate in construction sites.
- It is difficult to track the presence of people real time on large construction sites.
- Also, it is virtually impossible to predict exhaustion and fall incidents.
- A person who health metrices are not good on a day should not be deployed in harsh climate outdoor activities and in hazardous areas where a fall can be fatal.

#### 4.1.5 Optimising Scheduling

- Problem is, to make the construction schedule practical enough to mimic real-life situation.
- There is always a quest to develop an optimised schedule.
- Predicting time and cost overruns in the schedule.
- Predicting risks and hedging/ adjusting the plan accordingly.

### *4.2 Proposed Conceptual Models (Analysis)*

#### 4.2.1 Reinforcement Steel

- Visualizing the reinforcement model in VR glasses to better understand the reinforcement design before tying the bars, this will reduce the errors in comparison to looking at a 2D drawing and tying.
- When the Bars are in place, a Light Detection and Ranging (LiDAR) scan is done. It will capture all physical parameters such as diameters, positioning of bars, lapping distances etc. in form of a point cloud.

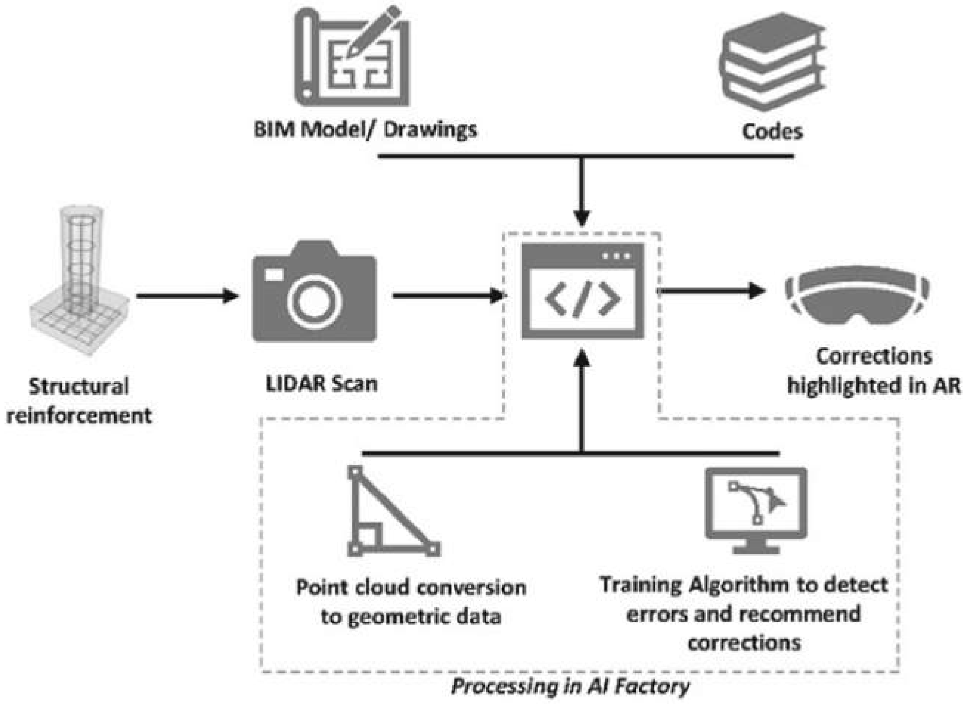



**Fig. 2** Reinforcement steel conceptual model

- Data cleaning through software and programming tools. Script is developed to keep only relevant data, filtering out irrelevant points which crowd the system.
- A trained AI algorithm (using our AIF platform) we compare the scanned virtual mesh to the BIM model/ Drawing.
- System gives decision support to site manager to give a go ahead for pouring concrete/or letting them know about the problematic areas for further manual verification.
- If there are any corrections, domain specific algorithm to recommend corrections. This will be visualized with the help of AR glasses to recommend corrections in the mesh (Fig. 2).

### 4.2.2 Temporary Support

- When the supports are in place, a Light Detection and Ranging (LiDAR) scan captures all physical parameters such as diameter of tubes, positioning of tubes, 'centre to centre' distance of supports, in form of point cloud.
- Data cleaning through software and programming tools. Script is developed to keep only relevant data, filtering out irrelevant points which crowd the system.
- A trained AI algorithm (using our AIF platform) we compare the scanned virtual mesh to input Codal provisions fed into it.
- The results are presented as a dashboard accessible through computer or handheld device. It gives site manager a go-ahead/or let them know about the problematic areas for further manual verification.

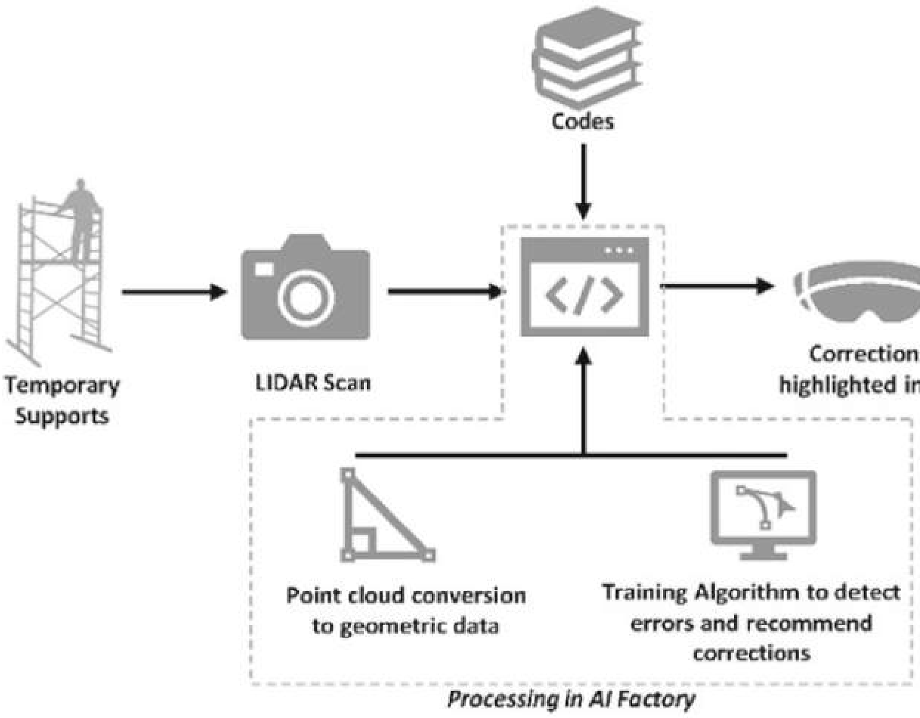



**Fig. 3** Temporary supports conceptual model

- If there are any corrections, we develop algorithms to recommend corrections. This will be visualized with the help of VR/AR glasses as per the suitability of data (Fig. 3).

### 4.2.3 Chat Con—Lesson Learned

- A chat bot tool for finding learning/experiences from all previous projects in the company could be a solution to this problem.
- It will also eliminate the need to browse through piles of documents to get access to learnings of interest.
- This Language learning model, inspired by the popularity of chatGPT, trained on private data can use all previous project lesson learnt experiences. It could give answers to challenges without consulting all the people involved in the previous projects (Fig. 4).

**Fig. 4** 'Chat CON' conceptual model

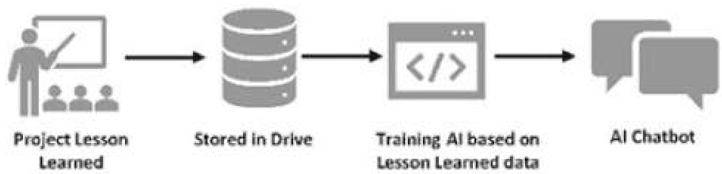
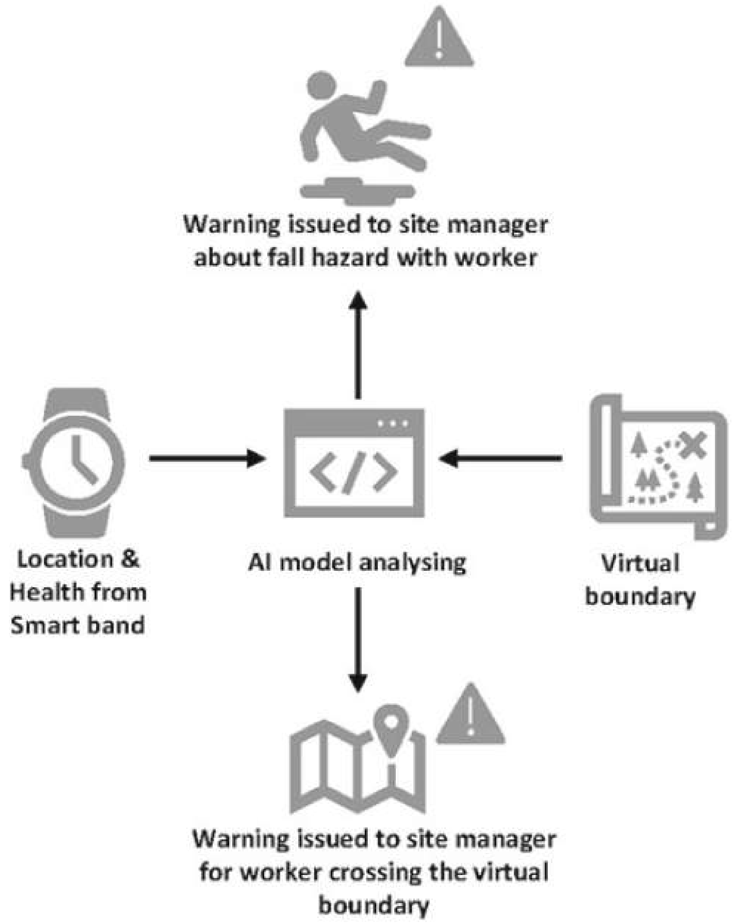


Fig. 5 Wearable device for location & health tracking conceptual model




### 4.2.4 Wearable Device for Location and Health Tracking

- A fitness band/ring kind of tracker will begiven to every worker on site.
- Temporary Virtual boundaries can be created on-site, and the location of workers can be tracked in real-time by AI, it can give a warning to the project manager about presence of people in the area before he/she approves the hazardous activity to start within the virtual boundary zone.
- Also, the AI-based tool can track health metrics of workers and predict if there is a hazard of fall associated with an individual that day. AI will give decision support assistance for manpower allocation to the site manager. Thus, substantially eliminating the probability of accidents on site (Fig. 5).

### 4.2.5 AI for Construction Scheduling

- Projects to utilise Artificial Neural Networks to anticipate cost overruns by considering various factors such as project size, contract type, and project managers' competence. By analysing historical data, predictive models can generate realistic timelines for future projects based on planned start and end dates.

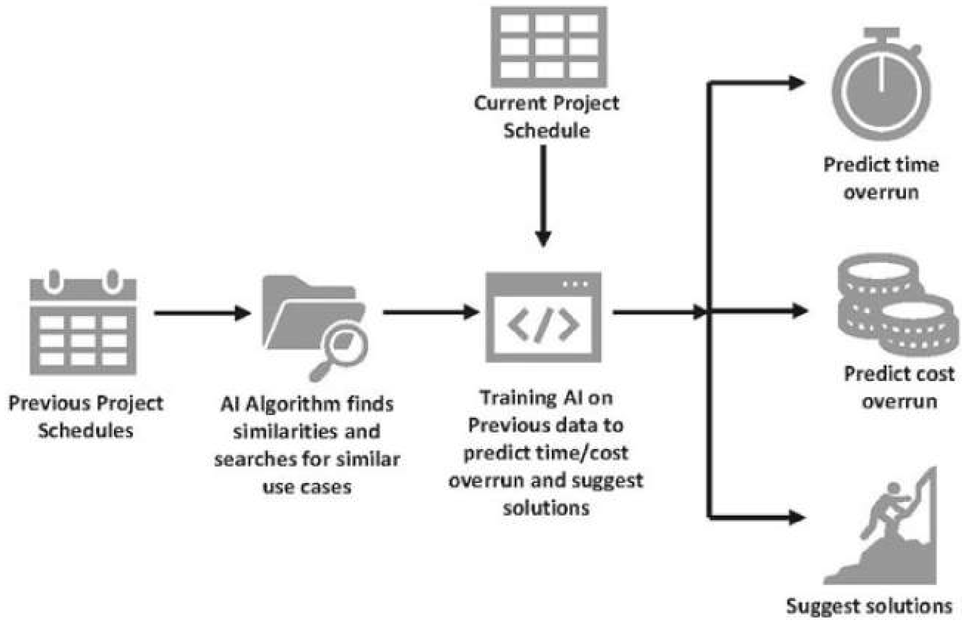



**Fig. 6** AI in construction scheduling conceptual model

- AI and machine learning solutions can be leveraged to monitor and prioritize prioritise risks at construction sites effectively. This enables project teams to allocate their limited time and resources to address the most significant risk factors. AI systems automatically assign priority to issues, while subcontractors are evaluated using a risk score, allowing construction managers to work closely with high-risk teams and mitigate potential problems. Consequently, this approach reduces overall risks and helps adhere to project schedules.
- AI models, utilising historical data and environmental parameters, can estimate workload values, takt times, and other relevant factors to synchronise the work cycles of both machines and human labour. By optimising processes and managing complex interdependencies among different trades, AI can contribute to streamlining operations and enhancing efficiency.
- Given below is a conceptual model but the detailed use case and its working mechanism needs to be explored in future steps of this research (Fig. 6).

## 5 Conclusion

In this research paper, we have explored the decision-making process of site managers in the construction industry and identified the challenges they face. We have also examined the potential of AI and digital technologies to assist in decision-making and proposed a set of conceptual models to support the site decision-making process.

The findings of this research provide valuable insights into the complexities that site managers face and offer innovative approaches to mitigate risks by improving decision-making efficiency and efficacy. By leveraging the models, site managers can benefit from automation, data analysis, and predictive modelling to make quick and informed decisions. These tools eventually have the potential to alleviate the stressful situations under which site managers operate.

The proposed conceptual models integrate hardware platforms such as LiDAR, Metaverse, AR, and VR with AI algorithms to enhance decision-making capabilities. These models enable tasks such as verifying executed components, ensuring the safety of personnel, accessing past project experiences, and adhering to schedules in terms of time and cost.

Further research and development are required to refine and validate the proposed conceptual models and integrate them into real-world construction practices. To further enhance the research, we intend to conduct a close ended survey with a larger sample size, involving domain experts, to establish a taxonomy of challenges. This taxonomy will aid in shortlisting the most relevant conceptual models for further investigation. Subsequently, demonstrators will be developed and deployed on construction sites to validate the selected use cases.

Overall, by addressing the identified issues and challenges through the implementation of AI-based decision support tools, the construction industry can potentially achieve improved efficiency, productivity, and project outcomes. This could be realised by harnessing the potential of AI and digitalization to optimise operations, reduce reworks and failures, ensure safety and security, and harmonise workflows.

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# Industrial AI for safety on construction site

**Purpose:** The construction sites are characterized by their dynamic nature, there are continuous changes and developments throughout the project. There are multiple factors which need to be considered to maintain onsite safety, one such case is the temporary structure. Temporary structures such as scaffoldings are commonly employed at construction sites to facilitate the provision of workspace. Although scaffolding is a crucial component on the construction site, it also poses significant risk which may lead to property damage, and injuries. The site manager is responsible for overall safety on site, to maintain a safe work environment visual inspection and evaluation is conducted at regular intervals.

Artificial Intelligence (AI) can assist the site manager to reduce the possibility of error in decision making. The purpose of this article is to employ AI for extraction of scaffolding structures and their representation for future comparison and assessment with established standards.

**Methodology:** The existing method for evaluating the condition of scaffolding relies on periodic visual inspections. The primary objective of these inspections is to assess the removal or addition of elements within the scaffolding system that could potentially impact its structural integrity. The proposed methodology focuses on topological representation of scaffolding structure with the aim of facilitating future evaluation and comparison.

Currently, LiDAR scanning is a popular method of acquiring spatial data of physical structures, due to reduced cost of equipment and sufficiently high resolution. LiDAR scanning results in point cloud data. Point cloud data is unstructured, and handling it is challenging because of the sparse and variable density. Even simple structures like scaffolding comprising of straight lines connected at nodes can require large amount of storage space in form of point cloud data.

Researchers have developed statistical, and machine learning methods, for extraction of scaffolding structure from the point cloud data. To conduct evaluations of scaffolding structures, it is necessary to have an appropriate representation of the structure that allows for comparisons to be made both initially against established standards and subsequently against any modifications made over a given timeframe. In this paper, machine learning segmentation methods are discussed to extract individual elements from the structure. The scaffolding can be conceptualized as a network of nodes and edges, leading to the utilization of existing data structures such as graphs for the purpose of representing and comparing these structures.

**Results:** This research gives a pipeline for processing the point cloud data and representing the extracted information as a graph to verify the potential structural changes in the scaffolding. The expected results from this study may offer a cost-effective and prompt approach for the continual monitoring of modification in temporary structures, which further increases the safety of the construction site.

Topics:

- Impactful AI
- Autonomous Monitoring
- Spatial Analytics

How does your proposal contribute to the AI theme of the conference?

This proposal promotes the adoption of AI technologies within the construction industry. Safety is a prominent issue on construction sites. This proposal aims to explore the potential of Artificial Intelligence (AI) in improving decision-making processes pertaining to scaffold safety through condition monitoring. The proposed approach incorporates technologies like LiDAR scanning and machine learning algorithms to automate the inspection of scaffolding and identify the potential structural modifications, thereby improving assessments with the goal of minimizing human errors and enhancing overall safety measures.

What might be new and innovative in your proposal?

The utilization of LiDAR and machine learning algorithms is not new, and previous research has contributed to detecting the scaffolding structures. This proposal initially identifies the different elements of a scaffolding structure. Subsequently, a comparative analysis is conducted over a period to ascertain that the temporarily removed elements are reinstalled. This process aids in evaluating the safety of scaffolding through continual monitoring. By employing this methodology, it becomes possible to eventually assess the structural integrity of the scaffolding in accordance with the established standards. The objective of this proposal is to utilize AI and automation to decrease the inspection time, enhance cost efficiency and safety of the personnel.

# AI as support for daily decision-making regarding scaffolding at construction sites

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## ABSTRACT

This paper explores the role of AI in supporting decision-making processes at construction sites, with a focus on scaffolding safety. Site managers must be able to balance safety, logistics, quality assurance, and risk management under critical time constraints. This study examines/explores how AI can improve decision-making in construction projects using scaffolding as an empirical case study. Scaffolding is a temporary structure critical for construction, and site managers must ensure it remains safe by identifying irregularities, confirming compliance with regulations, and taking corrective actions. The decision-making process for ongoing supervision of scaffolding involves three steps: identifying changes, verifying compliance, and acting, all of which require both practical experience and knowledge of regulations. The study is carried out partly through observations at a demonstration of AI applications for decision support, partly through semi-structured interviews, with on-site management personnel from construction companies. The study shows that AI can improve decision-making by processing large amounts of information quickly, and hence improving decision-making related to cognitive limitations, time constraints, and information availability. However, to trust AI-tools, as a help and support in decision making, the AI needs to prove itself reliable as the site manager will still be the decision maker.

## Keywords

Keywords: AI support, bounded rationality, construction site management, decision making.

## 1. INTRODUCTION

For site managers on a construction sites, there are many considerations and decisions to be made throughout a working day. Site managers most often work under high time pressure where safety is a crucial aspect to consider (e.g [1], [2]). At the same time, tasks and logistics must be controlled and coordinated so that the time schedule and budget can be met. Decisions in relation to quality assurance and the risk of committing mistakes adds to the pressure. The risk of human errors due to lack of time to take in and consider information to make sound decisions is continuously present.

Decisions can be categorized in programmed and non-programmed decisions [3]. The programmed decisions are well defined and have standardised solutions for problems that arise and are in this perspective closer to daily management and operations. Non programmed solutions are related to development and change, where there is a lack of already known solutions and alternatives. In this study, focusing on daily management from the site managers perspective, we are dealing with programmed decision making using the terminology of Daft [3].

Scaffolding at construction sites is used as a temporary construction aimed at enabling the permanent building to be constructed. There are codes and regulations, and design rules, for how to assemble the scaffolding. The site manager is responsible for continuously verify that the scaffolding remains the way it was assembled. If a change occurs, intentional or unintentional, the scaffold again needs to be confirmed. Such changes may be difficult to detect and are time consuming since they are done manually, yet very important for safety reasons [4]. Site managers' decisions process concerning scaffolding are made in three steps: firstly, to identify any irregularities or changes. Secondly, to confirm that the scaffolding is according to set rules and regulations, and if not, third, take actions to ensure safe scaffolding and safe work.

AI increases the ability to handle large amounts of information and data for analysis and decision making (e.g. [5]). This has already been shown in the field of medicine such as cancer research [6]. From this knowledge we realise that AI will enable to both collect, analyse and learn from large amounts of information which would reduce the time and accuracy in source and basis for taking decision about safety and quality at a construction site.

Using AI can streamline daily management at a construction site and simplify decision-making. AI can gather information to serve as the basis for decisions, analyse the collected data, and provide alternatives and suggestions to support decision-making in less time than any individual could [7].

In this paper we explore decision making in the context of temporary constructions with focus on scaffolding. Focus is to examine how use of AI could support systematic, sound and rational decision making. We use a case of scaffolding albeit the learnings could also apply to uses of AI in other site management decision making contexts.

The following research questions (RQ) have been formulated:

RQ 1 How could AI support decision making for construction site management, regarding:

- trust,
- usability, and
- boundaries (amount of information, cognitive ability to analyse, time constraints)

RQ 2 What heuristics biases will be possible to address and reduce through AI?

This paper presents results as a part of a larger research project. The larger research project´s aim is to develop an AI tool to a prototype level, for site management to use as a support for daily decisions about scaffolding. The research project has worked closely to two different companies and two of their projects and site management teams. The site organisation has been involved and included in defining what challenges they meet, and the researchers have developed the AI tool to meet these challenges. This means that the development has taken its starting point in the construction sites' situation and context. In this paper focus is to understand how the developed AI tool would help in their daily management and decision process. Throughout the project, involved managers have been presented the developed tool in demo-workshops. Site management have then been given the opportunity to ask questions and test usability and relevance.

## 2. THEORETICAL FRAMING

In the category of programmed decision making, classical rational decision-making is commonly used and assumes that best decisions are made based on complete information and the existence of clear alternatives for well-defined problems [3]. Daft [3] highlights that organizations need to process information – meaning gathering and analysing information – to reduce uncertainty and ambiguity in decision-making. This rational decision making is linear and follows a logic often described as intelligence, design, choice and implementation [8], [5]. Therefore, more information leads to better decision-making, but in reality, there are limitations and boundaries. These boundaries, or limitations stem from limited cognitive capabilities, time constraints and incorrect and insufficient information [3]. The cognitive limitations refer to individual's capacity of processing information, time limitations relate to the amount of available time for analysing and decision making, and the third limitation relates to the actual available information. Analog information management is limited by individuals' and organizations' capacity to handle large volume of information and conduct analyses and make decisions. The results, the decisions taken, have hence been either satisfying or good enough decisions rather than the best possible decision according to theory [3]. When it comes to what really happens in decision making the individual and behavioural perspective plays a crucial and decisive role.

A behavioural perspective on decision-making emphasizes that decisions are rarely based on objective information and facts. Instead, decision-making is heavily influenced by judgments that rely on simplifications and heuristics, which are linked to individual experiences and knowledge [9], [10]. Even in cases where factual data and statistics exist, heuristic judgments often lead to biased decisions (ibid). Kahneman [11] introduced two separate systems for making decisions. System 1 is fast and based on intuition and heuristic judgements. Being fast and intuitive, decisions made in system 1 are error prone. System 2 is a slower decision-making procedure, using facts, analysis and reflection prior to a decision. In system 2 decision making results in more thoughtful and reliable decisions. As human beings, we are prone to take the easy way, using System 1 at the risk of errors and biases. Relying on intuition and heuristics when using system 1 [9], [11] instead of taking in complete, and adequate information, is risking leading to quick but wrong decisions most often called human errors. The risk of human errors is as well related to situation and timing [12]. To better understand the difference in errors that could occur, we relate to Rasmussens [13] performance levels: Skill-based level, Rule-based level and Knowledge-based level. Skill-based errors are slips and lapses due to inattention or lack in following routines and regulations. Rule-based errors relate to using faulty recommendations or routines related to not understanding information or lacking the ability to match available information to the appropriate action. Errors and mistakes at the knowledge-based level stem from an inability to understand or comprehend new information that renders old rules and routines obsolete, necessitating new solutions. The issue lies in the inability to recognize that new information or rules are needed to replace or correct inadequate old ones. Decisions at this level aim for non-programmed solutions and are therefore not included in this study.

Kahneman [11] and Reason [12] argue that more information does not necessarily lead to better decisions. As individual decision-makers, we tend to rely on System 1, making decisions at skill-based and rule-based levels. Additionally, individuals often justify their decisions retrospectively, based on what suits them at the moment and in the given context.

To support a rational programmed decision making leading to reliable and less error-prone outcomes, the ability to analyse the information is essential. For a more reliable decision the combination of sufficient and available information, cognitive ability to analyse that information and time to do those previously mentioned is crucial.

## 3. METHOD

To be able to answer our research questions, we have chosen a qualitative approach where understanding and exploration are in focus.

The execution of the research is summarized in following four steps:

**Step 1 – The tool**. As input for the study there was a prototype of a tool developed within the larger research project. The tool aims to be able to compare the status of the scaffold at different times. This is done, in simplified terms, by using Lidar to scan the physical scaffold into a digital model at different times and then using developed algorithms to identify parts and nodes in the scaffold. The tool can then identify discrepancies between the models, that could constitute potential errors.

**Step 2 – Demo**. The respondents in the survey participated in a demo/workshop where they were given a presentation of how the tool works and how it is intended to provide decision support for the site manager regarding scaffolding. The respondents also tested different types of technical support tools where they could navigate and move around the models themselves.

**Step 3 – Interviews**. Semi-structured interviews were held with each of the respondents. The interviews covered three areas of inquiry: 1) Collecting information on status of scaffolding, 2) Analyzing available information and 3) Support to make decisions for action. The three areas of inquiry were examined partly from the perspective of how scaffolding is handled today, and partly from the perspective of how it would work with the described and demonstrated tool, including the respondents' expectations on future AI applications.

**Step 4 – Analysis**. Analysis of the interview transcripts was carried out by the two authors, with a combined knowledge of Site management and digitalization within construction, which enabled qualitative findings from interviews and observations. The analysis has been carried out in three steps. First, the interviews were transcribed using the MS Teams function. Secondly, the content of the material was analysed by reading and highlighting statements connected to decision-making, both regarding the perceived limitations in today's way of working with scaffolding and regarding AI's possibilities to overcome the limitations. Key phrases were noted in a spreadsheet sorted by respondents and for each question area. In the third step the key phrases were sorted into categories within the theoretical framework regarding bounded rational decision making and theories on human error.

Our respondents are three site managers, one production managers (head of site managers) and one project engineer working as administrative support to the site manager, giving a total of five respondents. All but one site manager are employed at a large firm.

# 4. RESULTS AND ANALYSIS

Our findings highlight both the current workflow as described by our respondents and their expectations of AI, as demonstrated in our presentations, se table 1.

**Table 1. Summarized responses related to collection and analysis of information in current workflow and in perceived expectations on future AI application.**

| ***Current workflow*** | ***Perceived expectations on AI*** |
|---|---|
| **Collecting information on status of scaffolding** | |
| Visual inspection by site manager on more or less regular basis. | Regular collection of information with help from scanning device |
| Looking at critical points based on previous experience and knowledge | Thorough information on deviations will be collected regardless where they appear |
| Trust on reports from individuals at site if something deviates from normal | Regular scanning with information of deviations |
| Time-consuming for human individuals, especially with large and complex scaffolding. | Possible to do at any time with little time spent by human individuals |
| **Analyzing information** | |
| Requires knowledge about design rules for scaffolding used at site to be able to confirm status of scaffolding and detect deviations | Using design rules from each applied scaffolding to detect deviations. |
| Using available information from visual inspection, ie what each individual are able to take in and relate to, to detect deviations. | Acknowledge deviations from originally mounted scaffolding that is certified as OK. |
| **Decision support** | |
| Need to rely on subcontractors and own ability to confirm a safe scaffolding | Support for decisions but not making decision. |
| | Need to prove itself as reliable before being trustworthy. |

## 4.1 Current workflow of managing scaffolding at construction sites

Site managers often hire subcontractors for both design and scaffolding assembly. Although all three respondents are certified to assemble scaffolding up to 9 meters, they still rely on subcontractors. The handover of responsibility for the scaffolding is done to the site manager, who contractually assumes this duty. The site manager is then obliged to continuously confirm that the scaffolding remains compliant with regulations as when delivered. Any modifications to the scaffolding require formal confirmation by the contracted scaffolding specialist or a return to its original status.

During the planning phase, site managers coordinate with subcontractors to ensure that the scaffolding facilitates an efficient workflow for the tasks to be performed on-site.

”I trust scaffolding builders who show load tables. A lot is in one’s head but the requirements are in the manual, the instruction manual is a standard.” (Site manager 1)

Checking and confirming the scaffolding status is a daily task for site managers. All respondents conduct visual inspections regularly, with frequency depending on scaffolding complexity. These inspections are usually part of the daily site review, not scheduled separately. Additionally, safety inspections with representatives focus on scaffolding every two weeks. During these checks, site managers look for changes and deviations based on past experiences and provided checklists.

“I look more at things that I have heard of or seen”…. “I especially check railing, planks, the crossing against the wall, the feet on the scaffold – the choice is linked to both experience and regulations.” (Site manager 1)

“I ensure the scaffolding feet are stable and the ground is firm.” (Site manager 3)

“The worst scenario is if someone disassemble a bar or railing and then neglect putting it back in place” (Site manager 3)

“You need to have a kind of trust in the people you work around, that they are your eyes out on the site too” (Site manager 3)

"We have great confidence that nothing has happened, and we do not expect any future incidents. Because of this, the likelihood of something happening again should be very small." (Site Manager 2)

Time management is a continuous challenge for site managers, indicated by our respondents. There are always events occurring and tasks to address, which make daily management including decision making challenging.

“Stressful to make decisions – do I have time to gather and analyze? I have to let go and prioritize what burns the most. Prioritizing all available time with my own time.” (Site manager 1)

“From time to time, I spend different amounts of time on checks. Sometimes you have a lot to do, then you prioritize other things.” (Site manager 2)

Previous incidents at sites often relate to weather and external conditions. A respondent described a near accident where where the weather protection caught wind and affected the scaffolding. After this incident, they added this risk to their control checklist.

## 4.2 Opportunities and expectations on using AI

Our respondents were all positive to digital support and see opportunities with access to the demonstrated AI tool. First and foremost, it is the time saving perspective that is attractive. To have an AI tool to identify deviations and changes on a daily basis, instead of manual visual control would save time.

Our respondents also acknowledged that an AI-tool as demonstrated would be able to identify all changes from the original, even small deviations difficult to see for a human eye.

"I look forward to how I can use AI's experience bank to find a good solution to scaffolding It would have been good if any deviations was lit up in red, letting me know where there are problems." (Site manager 1)

Being positive to using AI does not however mean that they are willing to let AI make decisions. There is agreement that AI can support and help in the decision process and any AI needs to prove itself reliable before being trusted by our respondents.

"I hadn't completely trusted the information – I would probably have double-checked before I get a relationship with my AI" (Site manager 1).

# 5. DISCUSSION

Decisions with well-defined solutions such as safety of scaffolding are categorised as programmed decisions, following a rational decision process [3] This is, in theory, a good model for how to make decisions of this character. To make sound programmed decisions calls for complete information and ability to analyse the same information. From our results, we find that the ability to collect and manage large amounts of information is in practice limited. Site managers in construction have the full responsibility for safety, production, quality and economy at sites. They constantly navigate and make prioritizations on how to spend their time. To cope their daily management they seem to use system 1 according to Kahneman [11]. Their heuristic bias are hence affecting their decision making. Use system 1 or 2 is not a conscious choice, rather something happening intuitively which we also find site managers do. They are not aware of what information they are missing as it hard to see how the scaffolding are deviating from the originally with the visual inspections they perform. They confirm that they trust in others to report deviations, they seek deviations in areas where they have previous experience from deviations and they trust in the historically statistics that confirms that most often thing are not going wrong.

Errors, due to lack of ability to collect or analyse relevant information is one consequence of not being able to make a sound decision. Examples of this in given in the results when the respondents talk about how weather and circumstances at the site change prerequisites for the scaffolding. From this example we learn that more accurate information would enable decision that reduce both risk and errors but still does not take away the fact that not knowing what you do not previously know, ie that knowledge based errors [12] needs to be handle differently.

As confirmed in our results individual rely on heuristic biases in decision making [9]. One of the biases found in this study is when site managers look for deviations based on their previous experience and knowledge. Using previous experience make the decision process quicker and hence is good for the site managers daily situation. The risk is however that with a small spread of experience, vital information that would be important for a sound decision falls out of the frame of available information to analyse. Another bias is the trust in possibly flawed statistics, assuming minimal risk. Ignoring new information can lead to incidents and errors due to incomplete analysis of relevant data.

Respondents are positive in their attitude that AI can save time by analysing information and finding deviations. They appreciate AI's ability to detect subtle anomalies, similar to its success in identifying breast cancer tumours [6]. However, they emphasize that AI must prove its reliability before they fully trust it.

# 6. CONCLUSIONS

Conclusions from this study will be presented as answers to our two research questions.

*RQ 1 How could AI support decision making for construction site management, regarding:*

- trust,
- usability, and
- boundaries (amount of information, cognitive ability to analyse, time constraints)

To trust an AI tool for daily management, it must consistently provide correct responses that align with individual experience and knowledge. Respondents are clear that decision-making responsibility will not be delegated to AI. They are positive about digitalisation and AI, focusing on output over usability, which is assumed to be a given.

Limitations in current decision-making could be mitigated by AI, allowing site managers to save time and receive accurate support. AI can systematically build and share experiences, providing a more reliable basis for decisions compared to checklists and personal knowledge.

*RQ 2 What heuristics biases will be possible to address and reduce through AI?*

Heuristic biases are used to facilitate quicker and easier decision making by humans. Our findings suggest that it is possible to address and reduce several heuristic biases in the bounded rational decision making of site managers. With AI support, a larger amount of information can be collected and analysed, thereby addressing time constraints as a boundary. This would reduce the need for shortcuts and reliance on "gut-feeling" and previous experience. The heuristic biases primarily addressed are the following:

- Confirmation biases can be decreased with the use of AI, which reduces interpretations of information that confirm prior knowledge, experience, and beliefs. AI and digital scanners collect more thorough information and relate and compare with previous, to find deviations and possible errors.
- Overconfidence bias is evident when individuals overestimate their ability, related to inadequate statistics, to take in and analyse sufficient information. AI can help

reduce individual variance in both perceived and real capacity in decision making, minimizing the risk of skill-based errors due to inattention, slips, and lapses.

- Availability bias can be reduced as AI does not limit analyses to recent events at the site but considers all available information provided.
- Representativeness bias can also be mitigated with AI assistance, as individuals can avoid getting stuck in old routines and experiences not relevant to the current situation.

## 7. ACKNOWLEDGMENTS

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# AI for enhanced Site Management: Integrating AI Decision Support for Scaffolding Inspection

***Summary***- On the construction site, the site manager role is challenging as the person requires to ensure aspects like progression of construction, cost, quality standard and safety. Construction cannot be carried without temporary support or scaffoldings. The site manager is supposed to verify the installations and approve them as safe to use. The aim of this work is to explore Artificial Intelligence (AI) tools to assist in the inspection of scaffoldings and help site manager in making decisions related to integrity of scaffoldings.

***Problem Statement***- Currently, scaffolding inspections are performed visually by the site manager specifically visiting the site just for the purpose of inspecting the scaffoldings. Through a semi-structured interview with the site manager, two significant issues were identified when inspecting the scaffolding. For accessibility purposes, workers remove the element of the scaffolding and do not reinstall them. Even if the elements are replaced, there are chances of little deviation from the original or certified scaffolding. AI can automate routine inspection of scaffolding and highlight areas of concern in a scaffolding. This allows the site manger to focus their attention on those specific regions.

***Solution and Results***- Using a LiDAR technology a 3D point cloud data of the original or the certified scaffolding is scanned. Additionally, data is gathered when performing a routine inspection to identify any inconsistencies. The point cloud data is shown in Figure 1 which consist of ground, vegetation etc. As shown in Figure 2, the point cloud data needs to be processed and cleaned to extract the object of interest which is shown in Figure 3. Iterative Closest Point (ICP) algorithm is used to identify any modifications made in the scaffolding scan (Figure 4) compared to certified one. Figure 5 displays the current scan when matches with certified scan in green colour while any modifications are reflected in red. The detection level of modification severity can be adjusted using a threshold value which a site manager can control to avoid many false positive. Scaffolding can be considered as a network of nodes which represents a joint and edges representing a rod. To represent a scaffolding in a graph data structure individual elements are extracted. The graph data structure representation of a scaffolding is shown in Figure 6. This representation will use the vast mathematical knowledge and assist to incorporate the design rules which are used while installation of a scaffolding to perform the integrity check. Using the AR/VR glasses site manager can visualize the scaffoldings and can only focus on areas where there is an issue which reduces the visual inspection errors. This eliminates the need for the inspector to be physically present at the site, saving both time and effort. The inspector may authorize the inspections of scaffolding remotely.

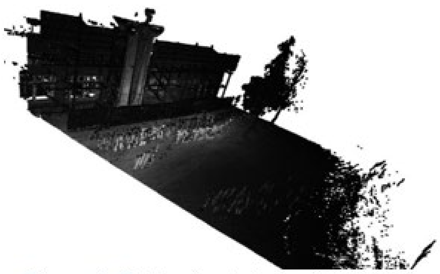

*Figure 1. Original point cloud data*

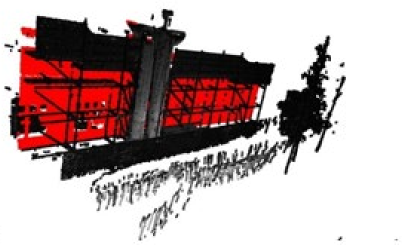

*Figure 2. Processing point cloud data*

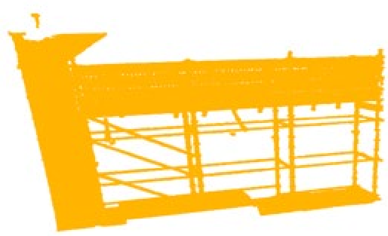

*Figure 3. Scaffolding extraction*

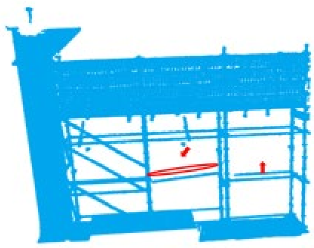

*Figure 4. Latest scan*

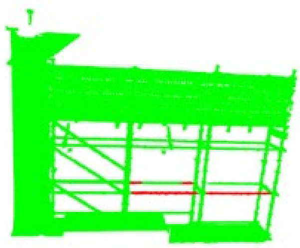

*Figure 5. Modification*

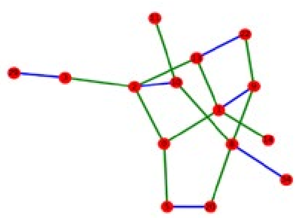

*Figure 6. Graph representation*

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# AI for enhanced Site Management: Integrating AI Decision Support for Scaffolding Inspection

***Sammanfattning***- På byggarbetsplatsen är platschefsrollen utmanande då det krävs att personen säkerställer aspekter så som konstruktionsutveckling, kostnad, kvalitetsstandard och säkerhet. Byggnationer kan inte utföras utan tillfälligt stöd eller byggnadsställningar. Platschefen ska verifiera installationerna och godkänna dem som säkra att använda. Syftet med detta arbete är att utforska Artificiell Intelligenta (AI) verktyg för att hjälpa till vid inspektion av byggnadsställningar och bistå platschefen med information för att kunna fatta beslut relaterade till byggnadsställningars säkerhet.

***Problembeskrivning-*** För närvarande utförs ställningsinspektioner visuellt med platschefen som specifikt besöker platsen enbart i syfte att inspektera byggnadsställningarna. Genom en semistrukturerad intervju med platschefen identifierades två viktiga problem vid inspektion av ställningen. För tillgänglighetssyften tar arbetare bort element i ställningen utan att sätta tillbaka dem. Även om elementen byts ut eller tillbakasätts, finns det chanser att avvikelser kan uppkomma jämfört med den ursprungliga eller certifierade ställningen. AI kan automatisera rutininspektion av ställningar och lyfta fram problemområden i en ställning. Detta möjliggör att platschefen kan fokusera sin uppmärksamhet på de specifika regionerna.

***Lösning och resultat***- Med användning av LiDAR-teknik skannas 3D-punktmolndata från original eller den certifierade ställningen. Data samlas även in när en rutininspektion utförs för att identifiera eventuella inkonsekvenser. Punktmolnsdatan i som visas i Figur 1 består av mark, vegetation etc. Figur 2 visar behovet av bearbetning för punktmolnsdata för att möjliggöra extraktionen av objektet i intresse som visas i Figur 3. Iterativ närmaste punkt (ICP) algoritm används för att identifiera eventuella ändringar som gjorts i ställningsskanningen (Figur 4) jämfört med en certifierad ställningsscan. Figur 5 visar två skanningar som har jämförts, där matchningen av den certifierade skanning visas i grön färg medan eventuella ändringar reflekteras i rött. Detektionsnivån för modifieringsgrad kan justeras med hjälp av ett tröskelvärde som en platschef kan kontrollera för att undvika många falska positiva. Ställningar kan betraktas som ett nätverk av noder som representerar en fog och kanter, vilket är en representation av en stång. För att representera en ställning i en grafdatastruktur extraheras enskilda element. Grafdatastrukturrepresentationen av en ställning visas i Figur 6. Denna representation kommer att använda den matematiska kunskapen och hjälpa till att införliva designreglerna som används vid installation av en ställning för att utföra integritetskontrollen. Med hjälp av AR/VR-glasögon kan platschefen visualisera byggnadsställningarna och endast fokusera på områden där det finns ett problem, vilket minskar de visuella inspektionsfelen. Detta eliminerar behovet av att inspektören är fysiskt närvarande på platsen, vilket sparar både tid och ansträngning. Inspektören kan godkänna besiktningarna och byggnadsställningarna på distans.

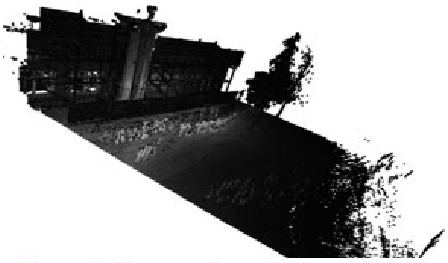

*Figure 1. Ursprungliga punktmolndata*

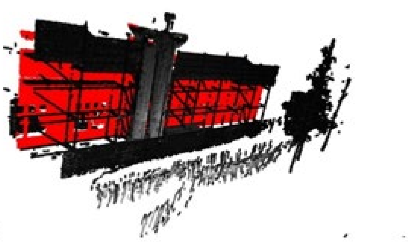

*Figure 2. Bearbetar punktmolndata*

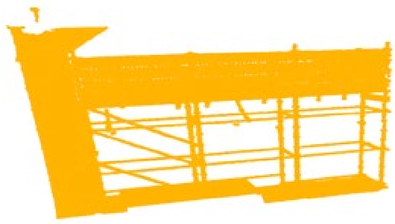

*Figure 3. Byggnadsställning*

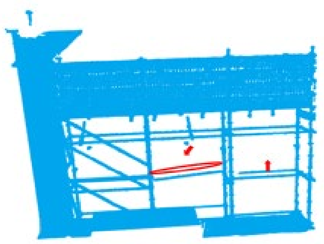

*Figure 4. Senaste skanningen*

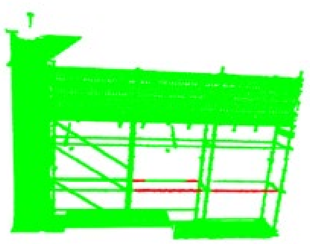

*Figure 5. Modifiering*

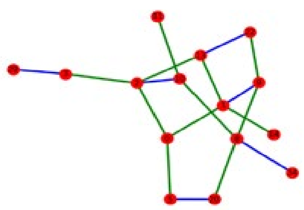

*Figure 6. Grafrepresentation*

# Enhancing Decision Support in Construction through Industrial AI


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## ABSTRACT

The construction industry is presently going through a transformation led by adopting digital technologies that leverage Artificial Intelligence (AI). These industrial AI solutions assist in various phases of the construction process, including planning, design, production and management. In particular, the production phase offers unique potential for the integration of such AI-based solutions. These AI-based solutions assist site managers, project engineers, coordinators and other key roles in making final decisions. To facilitate the decision-making process in the production phase of construction through a human-centric AI-based solution, it is important to understand the needs and challenges faced by the end users who interact with these AI-based solutions to enhance the effectiveness and usability of these systems. Without this understanding, the potential usage of these AI-based solutions may be limited. Hence, the purpose of this research study is to explore, identify and describe the key factors crucial for developing AI solutions in the construction industry. This study further identifies the correlation between these key factors. This was done by developing a demonstrator and collecting quantifiable feedback through a questionnaire targeting the end users such as site managers and construction professionals. This research study will offer insights into developing and improving these industrial AI solutions, focusing on Human-System Interaction aspects to enhance decision support, usability, and overall, AI solution adoption.



## Keywords

Decision Support, Construction Industry, Industrial AI


## 1. INTRODUCTION

The construction industry adheres to a well-defined and systematic phase to ensure project success. For informed decision making and resource allocation, project leader depends on data. Although new advanced technologies are being integrated in the construction process, their adoption remains limited. However, more companies are now opting for advanced technologies including AI and automation to have a competitive advantage in the industry [1]. The success of a construction project is usually measured by four indicators including cost, schedule, quality and safety [2]. The construction industry follows a structured process which can be divided into four phases [3], shown in **Error! Reference source not found.**. Each phase plays a crucial role in successful execution of the projects. The first phase is the planning or the initiation phase, during which project objectives, feasibility assessment, budget proposals and scheduling are performed. It is essential for establishing project directions and to prevent delays and budget overruns. During the design phase, blueprints and specifications are created in accordance with the building codes and safety regulations. The production phase includes the execution of actual building activities, involving tasks from material logistics to safety compliance. This phase is labour-intensive and requires real-time decision-making. The long-term sustainability and operational efficiency of the structure is ensured through the management phase.

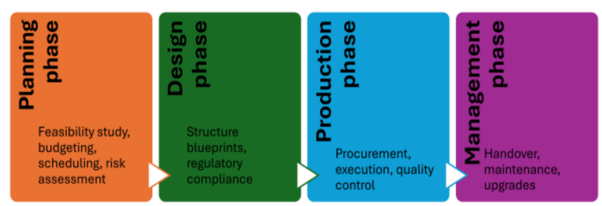


**Figure 1. Construction Phases**

For the scope of this study, we focus on the production phase as it emerges as a critical phase where decision-making significantly impacts the project outcomes. This phase is often complex in nature as it includes material handling, resource management, equipment operations, and safety compliance. Accurate and timely decisions are essential in this phase to control the cost and ensure project deadlines and the safety of on-site activities. Therefore, enhancing decision support during this phase is essential to improve the overall project performance.

Artificial Intelligence (AI) term was introduced in the 1950's and since then it had seen shifts in the level of interest by scholars and practitioners [4], [5]. Advanced digital technologies, particularly AI are transforming industries, and have successfully been utilized to enhance efficiency, safety and security. However, along with benefits of AI applications, certain challenges relevant exist in the construction industry [6]. AI is developing as a revolutionary force across all the phases of construction. The production phase presents unique opportunities and challenges for the integration of AI-based solutions. On a construction site, the site manager faces various dynamic and unpredictable situations requiring informed decision support. AI-based solution has the potential to assist the decision-making by analysing and identifying patterns within the data. Despite the potential, the adoption of AI solutions remains limited due to challenges like trust, security, expert shortages, and computing power requirements [6]. A successful adoption and integration of AI requires a fundamental understanding of both functional and non-functional requirements. This requirement analysis ensures the identification of both technological capabilities and human-system interaction (HSI) needs of the system.

This paper explores the functional and non-functional requirements of the users of AI-solution by understanding their insights and feedback. This is to ensure their needs and challenges are addressed during the development of the AI system and to enhance the Human-System Interaction. The technical capability of AI is emphasised when developing the solution, often overlooking the human-centric design principles necessary for a successful and effective adoption. To bridge this gap, this research aims to identify and describe the key factors and their correlations when developing industrial AI solutions that are both technically robust and user-friendly. Focusing on end-user perspectives and collecting quantifiable feedback through a demonstrator and questionnaire, this study can provide a foundation for creating an industrial AI system.

## 2. Background

Digitalization and AI technologies in the construction industry have been adopted to enhance productivity, optimize operations, improve site safety and security [7]. However, [6] highlights that the construction industry lags behind compared to the manufacturing and telecommunication sectors. AI in the construction industry is used to automate planning and scheduling, safety management, smart construction [6]. [8] focused on technical capabilities of AI, including machine learning and big data for large datasets predicting delays, optimize scheduling. Machine learning to help in safety and risk management, AI-powered generative design. A comprehensive review of applications of AI in the construction industry is given in [7]. Machine learning algorithms like neural networks, and support vector machines, were used for cost predictions, and risk analysis whereas for safety assessment and decision support expert systems, rule-based systems were mentioned [7]. The impact of AI on project management, risk management, cost control and scheduling were discussed in [9]. AI enables optimized resource allocation, real-time monitoring and predictive analytics [9]. For automated code compliance checks, Natural Language Processing is being tested to extract information for regulatory texts [10]. From the past construction management project documents AI could enhance information retrieval hence facilitating decision-making easier and faster [4], [11]. AI technologies like machine learning and artificial neural networks possess the capability to manage explicit and tacit knowledge in construction projects for the encoding of visual building information [4], [10].

Despite the benefits, adopting AI in construction is challenging. Due to high complexity and fragmented workflows, the adoption of AI is limited [9]. The high initial costs, limited digital infrastructure, and lack of skilled AI professionals in the construction sector are some other challenges mentioned in [9]. Construction managers find AI solutions too complex and difficult to understand, leading to low adoption [12]. As the existing workflow relies on manual processes and legacy systems, there is resistance to change from the traditional system [13]. Construction projects involve multiple stakeholders, making data integration difficult; uncertain guidelines on AI applications create uncertainty; data security and privacy create additional barriers [14].

[15] acknowledges the importance of requirement analysis when implementing performance-based building (PBB) approaches to enhance innovation in the construction industry. [16] suggested that successful AI adoption requires emphasis on Human-System Interaction, indicating that AI solutions should be designed with the end-user's workflow in mind rather than only technical innovation. To facilitate AI adoption [16], [10] explore approaches emphasizing usability, decision support and human-AI collaboration. Challenges like user acceptance, trust, and interface complexity have frequently left construction professionals often reluctant to integrate AI-based tools [17]. AI solution is more likely to have higher usability and acceptance if it integrates seamlessly into existing workflows [17]. In order to facilitate AI adoption, several key indicators have been suggested, to increase trust in AI systems, transparency, and explainability should be increased [18], [10]. The construction site has dynamic conditions, and AI tools should be adaptable and evolve based on user experience. Human experience remains crucial for complex decision-making, whereas AI systems are best suited for repetitive tasks. [18] recommends a hybrid AI system that integrates AI-driven insights with human judgement. Organizations must prioritize the reskilling and upskilling of personnel to facilitate collaboration with AI systems. To enhance productivity, and improve decision-making, human-AI collaboration needs to be implemented [18].

## 3. Research Methodology

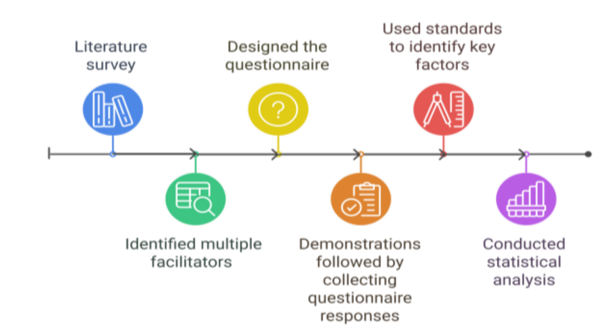


**Figure 2. Research methodology followed in this study**

This study combined qualitative and quantitative research approaches to ensure a comprehensive exploration. We opted for a mixed-method approach as it was suitable for analysing both, quantitative measures and subjective experiences. This provided us with a holistic understanding of the analysis. Our research methodology included a literature survey, demonstrations followed by a questionnaire, semi-structured interviews and thematic analysis to identify the key factors to facilitate the adoption of AI and hence enhance decision support in construction.

### *3.1 Literature Survey*

The study began with an exploratory literature review to provide a theoretical foundation. This was done to identify relevant research trends, gaps, and key factors related to the adoption and success of technological tools including AI to enhance decision support in the construction industry. The literature search focused on the abstracts of articles within the 2022-2025 period, and the searched keywords included “construction industry” AND “decision support”. The search provided 83 articles from Scopus and 66 articles from Google Scholar. Duplicate articles from both searches were removed, and a scope assessment was done to avoid unrelated articles. Additionally, a backward citation analysis was done. Articles from the initial search were reviewed for their reference lists to identify additional relevant articles. A total of XX relevant articles were reviewed in this study.

### *3.2 Demonstrations and Questionnaire*

Based on the gaps and factors identified from the literature survey, a questionnaire was developed in reference to a demonstrator, showcasing the use of Industrial AI in the construction industry. The developed questionnaire was structured into two types of questions and supported English and Swedish languages. Following the work of [19], which states that Likert-scale questions are commonly used to measure perceptions, and experiences of participants in a survey due to their ability to capture varying degrees of opinion and ease of analysis. Therefore, most of the designed questions were on a Likert scale with a few on 5-point scale (ranging from "Strongly Disagree" to "Strongly Agree") and a few on 10-point scale (ranging from rating 1: Not at all likely to 10: Extremely likely). However, a few questions included text fields to collect user suggestions and feedback. To ensure a clear understanding among the participants, a presentation on a developed demonstrator was given followed by a hands-on experience with the AR/VR glasses to interact with the developed tool. The developed demonstrator illustrated the potential use of Industrial AI for assisting site managers as a decision support tool. It was developed in reference to a scaffolding on a construction site. These demonstrations explained the system’s workflow, emphasizing the key stages starting with data acquisition, data processing, and finally, visualization. The demonstration consisted of the following steps:

Data Acquisition:

This step explained the use of a handheld LiDAR scanner to scan and collect the 3D point cloud data from a construction site, a scaffolding in this case. LiDAR technology was selected in developing this demonstrator due to its precision in capturing 3D point cloud data.

Data Processing:

This step involved processing the raw data from the LiDAR scanner and optimizing it to reduce computational load using data filtering and point cloud compression. It enhanced the computational efficiency of the scanned model enabling their smooth rendering in the AR/VR glasses.

Visualization in AR/VR:

In this step, the processed point cloud model was rendered using Azure Remote Rendering services in AR/VR glasses. The digital model simulated the real-world construction site. This was done to demonstrate the practicality of the technology and to highlight the potential use of such tools for remote collaboration. It also highlighted how intuitive and interactive systems facilitate a deeper understanding of its capabilities in construction workflows.

The demonstrator was developed not only to showcase the potential applications of the technology but also to encourage the participants to brainstorm and reflect on the challenges associated with its implementation in real-world construction scenarios.

Nineteen participants filled out the questionnaire. The participants were intentionally selected from a diverse range of backgrounds and experience levels with respect to the construction industry and experience with technologies. The participants consisted of 15 males and 4 females, with a wide range of ages and professional backgrounds. Nine participants were between 18-25 years, two were in the 26-35, 36-45, and 46-55 age groups, one was over 55 years old, and one participant preferred not to disclose their age. The group comprised 10 final-year construction students with on-site experience and 9 professionals with a mix of academic and industrial backgrounds with respect to the construction industry. This group of professionals included researchers, professors, site managers, production managers, and branch and association managers specializing in construction and technology integration.

### *3.3 Semi-structured interviews*

Semi-structured interviews were chosen to gather qualitative insights from the participants. This approach was chosen because it provides flexibility in exploring predetermined topics while allowing the possibility of open-ended discussions with the participants [20]. The interview questions focused on the participant’s insights on the production phase of the construction process. The discussion included the intention of understanding the role of humans in the subprocess in the production phase and their insights on having an AI-based system to assist humans in decision-making. The interviews were also directed towards gaining their suggestions in areas where AI could help and if so, what could be the limitations in its successful adoption. Additionally, participants were also asked to discuss the areas where they think traditional practices were enough and adopting AI solutions would not be very beneficial. The interviews also focused on gaining insights from the participants on the limited adoption of AI in general in the construction industry.

### *3.4 Data Analysis: Thematic Analysis*

The data collected from the literature review, questionnaire responses and insights from the semi-structured interviews were analysed using a thematic analysis approach. Thematic analysis was chosen for this study as it is a commonly used qualitative method for identifying, analysing, and identifying themes or patterns in data [21]. After careful analysis and interpretation of the collected data, findings were aligned with the relevant standards [22] to identify the key factors.

## 4. RESULTS

This section reveals the key insights into the perceptions of incorporating AI in enhancing decision-making in the production

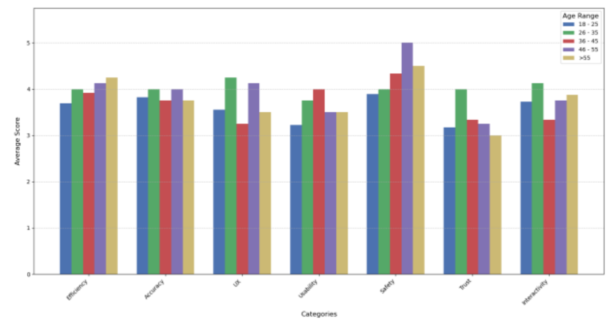


**Figure 5. Key factors score by age group**

phase. The results are broadly classified into 4 headings as discussed below:

### *4.1 Identifying key factors*

Using established standards and thematic analysis, discussed in section 3.4, key factors which are required to incorporate AI to enhance decision-making are identified. These indicators include efficiency, accuracy, user experience (UX), trust, usability, safety, and interactivity. These key factors impact both system performance and user acceptance and are critical for the successful adoption of AI. These factors comprise the functional and non-functional requirements. Accuracy, safety, and interactivity could

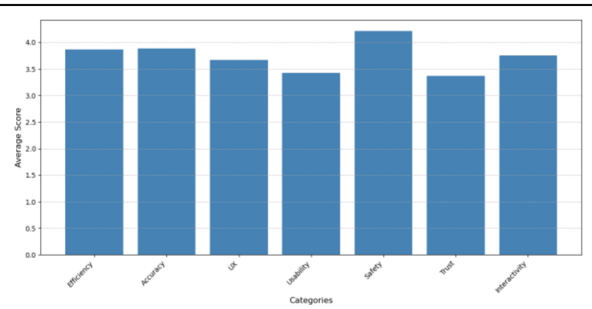


**Figure 4. Key factors mean score**

be identified as functional requirements. These factors define the essential capabilities that the system must have. Meanwhile, efficiency, user experience (UX), usability, and trust could be classified as non-functional requirements. These factors focus on how the system operates and supports user interaction. Optimizing these key factors while developing AI solutions can enhance decision-making.

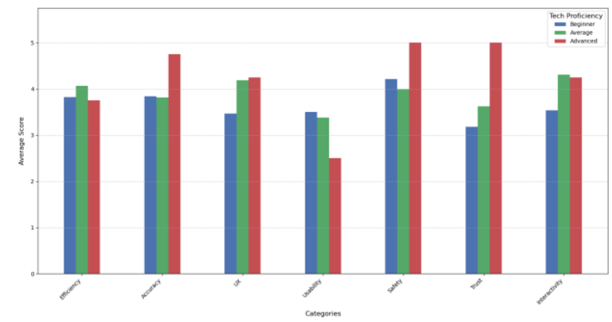


**Figure 3. Key factors score by technical proficiency**

### *4.2 Score across key factors*

The average score for various key indicators is analysed and shown in Figure 3, emphasizing the critical role, safety received the highest score. Trust scored lower than other key factors, reflecting concerns about the confidence and reliability of the AI solution. Other key factors have a moderate score, suggesting future potential with further improvements and optimizations.

### *4.3 Variations in key factor scores*

In this section, the scores for key factors are further analysed based on professional and demographic differences.

#### *4.3.1 Scores by age group*

As shown in Figure 4, participant's perception varies across different age groups.

Safety and efficiency are rated high by participants over 55 years of age; however, they gave lower scores in trust, usability and interactivity, suggesting hesitancy toward adopting new technologies. Given the sample size, the participants provided moderate scores across all categories, indicating a balance between openness to technology and caution. However, during the semi-structured interviews, safety was emphasized as the primary concern, which is also reflected through data analysis. Middle-aged participants are more receptive and comfortable with technology compared to the older age group.

#### *4.3.2 Scores by technical proficiency*

Figure 5 illustrates the relationship between technical proficiency and key factor scores. Participants with advanced proficiency indicate confidence in technology's capabilities reflected through high scores in accuracy and interactivity. Beginner-level proficiency gave lower scores on trust and usability, suggesting a limited understanding of AI capabilities.

### 4.3.3 *Scores by profession*

The key factor scores between students and professionals are shown in Figure 6.

Professionals rated safety a high score, reflecting their focus on risk management and reliable operations whereas students showed greater interest in the ease of use and engagement provided by technology gave higher scores for the interactivity key factor.

### 4.4 *Issues and suggestions for site managers*

A word cloud is presented in Figure 7, summarizing the issues and suggestions mentioned by the participants. Maintaining safety working conditions is a critical concern, effective planning, regular inspection rounds and managing dependencies are seen as elements to reduce delays and conflict on site.


**Figure 7. Word cloud of issues/suggestions for site managers**

## 5. CONCLUSION

The key factors influencing the adoption and acceptance of technology including AI in construction's production phase are identified in this paper. These factors were categorized into functional and non-functional requirements. Accuracy, safety, and interactivity were identified as functional requirements, defining the essential tasks and core operations the system must perform. In contrast, efficiency, UX, usability, and trust were classified as non-functional requirements, emphasizing how the system should operate to support user engagement and effective interaction. As reflected by both data analysis and semi-structured interviews, safety is the top priority. AI solutions that prioritize safety when dealing with critical and high-stakes tasks are likely to gain trust and acceptance. Particularly in the older generation, the key factor of trust remains a significant barrier to AI adoption. However, increased transparency, gradual integration of automation, tailored training and support programs can help build confidence in the users. The generational and proficiency-based difference in perceptions towards AI is also revealed in this study. Greater acceptance of technology, focusing on interactivity is exhibited in younger and technically advanced participants, whereas older and less proficient participants prioritized safety and expressed hesitance in AI adoption. These findings contribute to enhancing decision-making processes and facilitating human-system interaction (HSI). This can ensure that the digital tools are user-friendly and intuitive to use. Improved HSI enhances usability and interactivity, helping users feel more engaged and confident in using AI-based systems. This interaction fosters trust and adoption, especially in environments involving complex tasks that require smooth collaboration between human and automated systems. Additionally, these findings can serve as a valuable base for a framework for assessing the technology readiness level (TRL), of AI and digital systems in construction workflows to evaluate the maturity of a technology.

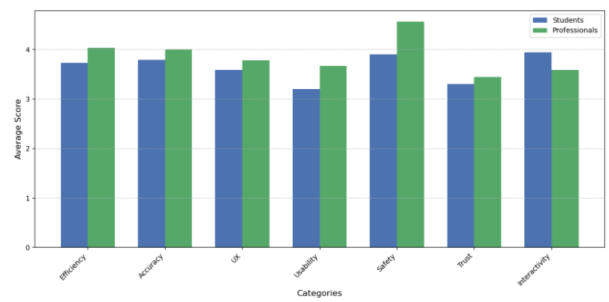


**Figure 6. Key factors score by profession**

## 6. ACKNOWLEDGMENTS

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# POINT CLOUD BASED MONITORING OF SCAFFOLDING: ASSISTANCE TO SITE MANAGER DECISIONS

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## ABSTRACT

In the construction industry, safety assessment is essential to ensure assets reliability and workers safety. Scaffolding is a critical asset which requires regular inspection to identify modifications that might compromise stability. Currently, visual inspections are conducted by site managers, this process is time consuming and can be prone to oversight. This paper proposes the use of point cloud data and Artificial Intelligence (AI) to automate the monitoring of scaffolding for safety assessment on construction site. By processing the point cloud data, scaffolding is extracted and then the proposed system detects any structural modifications, assisting site manager in decision making. This approach not only enhances the safety on a construction site but also reduces the time and effort needed for a manual inspection. Furthermore, this paper discusses steps for representing a complex scaffolding point cloud data in an efficient and structured manner using a graph data structure. This method may enhance the computational efficiency and structural analysis by capturing scaffolding connections and spatial relationships.

## 1. INTRODUCTION

Ensuring the safety of workers on a construction site is crucial, and this requires regular inspection and maintenance of the assets to prevent accidents. In accident causation model (Heinrich, 1941), the two causes of accidents are unsafe conditions and unsafe actions. Monitoring these two causes can reduce the risk related to safety on a construction site. Due to the dynamic working conditions and complex nature of a construction site, workers are increasingly exposed to hazardous environment. Identifying the causes of unsafe conditions, actions, examining equipment's, performing a safety inspection are the activities that come under safety and health monitoring (Reese & Eidson, 2006). Accidents occurring on a construction site have resulted in fatalities, damage to assets, harm to workers, financial loss and delays (Hamdan & Awang, 2015).

One of the important assets which involves safety-related risks is scaffolding. Most of the construction is conducted with the aid of temporary support or scaffolding. It is composed of steel tubes and joints, and the tube axes describes the spatial positioning. Factors that influence accidents on a construction site are subject to change from time to time (Hamdan & Awang, 2015). Accidents can be due to construction errors, inadequate protection equipment, poor technical conditions, excessive loads on scaffoldings, lack of complying components, inappropriate bodily actions, distraction, and other factors (Ismail & Ghani, 2012; Whitaker et al., 2003). Temporary structures can cause damages of life and cost because of collapses (Swedish Work Environment Authority, 2016). Scaffoldings are widely used on a construction site and according to (Swedish Work Environment Authority, 2016) requires strict adherence to safety protocols. To ensure good working condition and safety of the workers operating at height a regular inspection and maintenance should take place. This ensures safety of the workers and pedestrians on and around the scaffolding from any kind of accidents.

The site manager plays a pivotal and essential role in coordinating and supervising the construction site, ensuring the safety of workers, on time completion and adherence to the budget. Site managers are responsible for the inspection and monitoring of the scaffoldings. Currently, the inspection of scaffolding relies mainly on manual observations (Cho, Kim, et al., 2018) which is inefficient and can be erroneous for a large and dynamic construction site. Also, visual inspection will give qualitative evaluation, such as elements of scaffolding are missing or not. It is difficult to get precise quantitative results on the deviation of the modified elements. Continuous monitoring of scaffolding to identify modifications and check for the compliance requires time and effort from the site manager. As the construction evolves and for a complex site, manually inspecting and monitoring scaffoldings becomes challenging and inaccurate (Q. Wang, 2019), which may pose a potential threat to the safety of workers and people

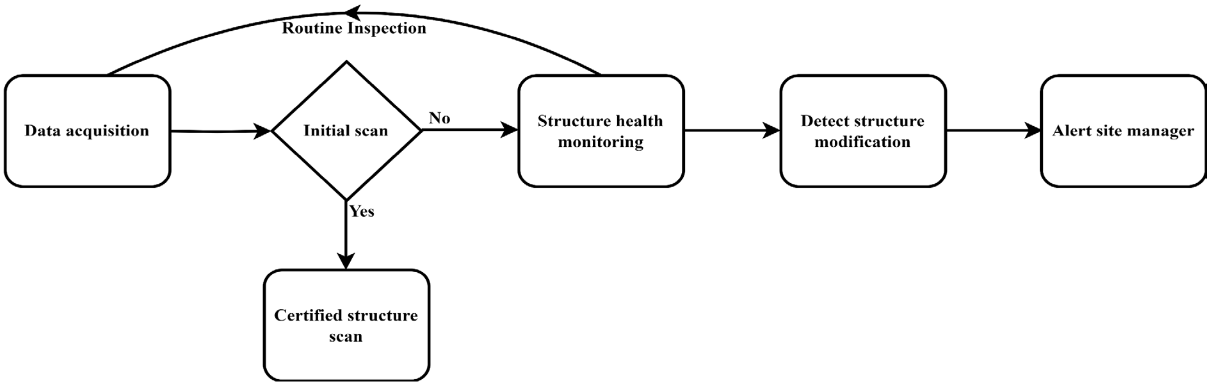



*Figure 1: Workflow*

positioned on and around the scaffolding. Continuous monitoring of scaffolding during the construction process is required, involving timely comparisons of the structure with the original structure which is according to the established rules to identify any modifications. Along with this, subsequently preform maintenance to restore the structural integrity is needed.

Prognostics and Health Management (PHM) is a method that focuses on the degradation mechanism of an asset to predict its health to optimize maintenance (Soualhi et al., 2022). PHM framework ensures optimal functioning, maximum reliability, and low maintenance cost of an asset. It involves steps like anomaly detection, wherein an alert is generated whenever real-time data crosses a pre-defined value. The next step is finding the probable cause for the deviation in values and, finally, prognosis to estimate the state of health (Soualhi et al., 2022). Sensors can be installed on the scaffolding to capture parameters (Moon et al., 2018), 2D image acquisition, or 3D point cloud data of the structure to collect information (Q. Wang, 2019). This data is analyzed and compared with a reference parameter to identify anomalies and flag them for further inspection. Figure 1 shows a broad view of this paper, which utilizes the concepts of PHM for asset health monitoring. The periodic data acquisition will be compared with the certified data to highlight the modifications in the structure. This paper proposes an approach to identify the modifications made to the scaffolding as the construction work progresses. This study utilizes a 3D point cloud data of the scaffolding to conduct a routine inspection aimed at detecting any changes by comparing the current scan with the original or initial scan. This will reduce the time and effort initially required by the site manager to perform scaffolding inspection. Additionally, the error caused by visual inspection can be reduced, thereby assisting site manager in their decision-making. The key contributions of this paper are as follows:

1. Proposing a method for monitoring scaffolding using 3D point cloud data. This facilitates the detection of structural changes that impacts its stability, hence enhancing the safety at the construction site.
2. An approach to represent the scaffolding using a graph data structure.

The rest of the paper is organized as follows. Section 2 reviews the literature on conventional and current approaches for inspection of scaffolding and identifies the research gap. Then, the following section 3 presents a methodology used for proposed approach with results in section 4. Conclusion and future direction of this study is in section 5.

## 2. STATE OF THE ART

## 2.1 Approaches of scaffolding inspection

Construction workers are often exposed to safety hazards, and monitoring the health of scaffolding structures is still premature (Cho, Sakhakarmi, et al., 2018). Depending on the load conditions, the boundary conditions, and material, design parameters vary which makes monitoring of scaffolding difficult. (Cho, Sakhakarmi, et al., 2018) uses wireless strain sensors to capture data from the scaffolding prototype and transmit it to a Finite Element Machine (FEM) model which estimates the real-time structural conditions. (Cho, Kim, et al., 2018) explores an integrated method for scaffold monitoring that connects components like strain data, finite element machine, machine learning, and scaffolding. The structural condition was collected using a strain gauge sensor, and a data-driven methodology was implemented to monitor the scaffolding. A finite element machine model was designed to simulate the structural response for a given load condition, and through this, training data for a machine learning model was generated using random loading cases. Lastly, structural conditions were classified as safe, overloaded, unevenly settled, and overturning using a machine learning model.

The inspection of scaffolding is labour-intensive and subjective, which may lead to inconsistencies. (A. Kim et al., 2022) aims to develop an automated inspection process using computer vision and machine learning. Both real and synthetic labelled datasets were used for training machine learning models to detect classes like rust, cracks, and deformations on scaffolding parts. (Chi et al., 2017) paper combines Building Information Modelling (BIM) and image processing methods to estimate the scaffolding progress by comparing it with site photos. The safety monitoring models are limited to specific hazards, but due to the dynamic nature of the construction site it becomes impractical for them to detect various hazards (N. Khan et al., 2021). Inspection of scaffolding is performed to ensure structural stability and workers' safety. Additionally, accidents might occur due to workers' behaviour while on the scaffolding. To detect workers' unsafe behaviours on a mobile scaffolding, (N. Khan et al., 2021) paper proposed an approach based on extracted correlation from safety rules. On the manually labelled images of scaffolding with and without outriggers, deep learning model for object detection and instance segmentation was implemented. The identification of workers unsafe behaviour was achieved by employing a combination of classification and segmentation of workers' tasks with an object correlation detection module. The object correlation module identifies the correlation between the predicted task with certain conditions. To reduce the risk of falls from height in the construction industry, (M. Khan et al., 2022) paper proposes a Smart Safety Hook monitoring system. This system integrates computer vision with Internet of Things based monitoring technologies. To identify workers and scaffolding from live-camera feed, deep learning methods were employed. If the algorithm detects the worker in a risk zone, Arduino Nano with an inertial measurement unit and altimeter sensor will activate to monitor the safety hook status.

The approaches mentioned above were mostly executed and tested on either a scaffolding prototype or a part of the scaffolding. Furthermore, the models rely heavily on the quality of the image data captured, which can be affected by the lighting and angles at which images are taken. Training of machine learning models requires the use of labelled data, which can be time-consuming and also the model's evaluation metric depends on the ground truth. All methodologies still require further development and validation before they can be used for real-world data.

## 2.2 LiDAR based approaches

3D laser scanning also known as Light Detection And Ranging (LiDAR) emits laser beams and detects the reflected signal from the target to measure the distance. Scanners which employ time-of-flight technique emits a laser pulse with a known velocity and measures the time travel of the reflected pulse. The distance to the target can then be inferred. LiDAR create a 3D map of physical space by measuring distances and spatial relationships between objects. 3D point cloud data acquired from laser scanning technology captures surface geometries in an accurate and efficient manner (Q. Wang et al., 2020). The technology offers high frame rates, wide field of view, and the capability to function in various lighting conditions, making it appropriate for dynamic and complex construction environments (Teizer, 2008).

3D point cloud data has become invaluable tool in construction, offering applications that enhance efficiency and accuracy through progress tracking, increases safety throughout the project life cycle using quality inspection (Q. Wang & Kim, 2019). (Styliadis, 2007), (Aydin, 2014), (Bosché, 2010), (Yu-Fei et al., 2016) used LiDAR technology to perform as-built inspection, quality assessment of buildings. From architectural objects like historical buildings and monuments, (Styliadis, 2007) paper aims to derive pictorial, geometrical, spatial, topological, semantic information. (Styliadis, 2007) discusses a practical demonstration of generating semantic models from high resolution images after calibrating and alignment to generate point cloud data. The semantic model integrates into computer-aided architectural design systems for further analysis. (Aydin, 2014) paper presents an approach of using high-resolution digital cameras and photogrammetry techniques to redesign building facades which has suffered from visual pollution due to urban sprawl. (Bosché, 2010) paper integrates 3D computer-aided design (CAD) and laser scanning technology to tackle the issue like progress tracking and quality control. The paper presents an approach to optimally register CAD models with site scan objects, and then calculates the as-built poses, facilitating control of dimensional compliance with specifications. (Yu-Fei et al., 2016) paper proposed a method to first obtain crack information from 2D images and then reconstruct into 3D scene using structure from motion (SfM) algorithm. This approach provides a blend of image processing and 3D modelling to monitor structural health.

The study conducted by (Oskouie et al., 2016) aims to reduces the time consuming, error prone manual inspection of highway retaining walls by extracting geometrical features from laser scan data to detect displacement in Mechanically Stabilized Earth (MSE) wall. Through point cloud data of MSE wall obtained at different time interval, (Oskouie et al., 2016) paper extracts horizontal joints which serves as the benchmark for measuring displacement. The current method of safety planning on excavation site that are prone to cave-in and falls are manual and error prone. (J. Wang et al., 2015) develops a semi-automated method by using geometrical properties of 3D point cloud data to identify fall and cave-in hazards. For better safety planning, hazards identified from point cloud data and required safety regulations was integrated with Building Information Modelling (BIM). Active safety systems which can detect hazards in real-time are essential for improving the safety on a construction site. (Teizer, 2008) explores the use of 3D range camera for accident avoidance on a construction site. Algorithms were developed to improve the ability of 3D range cameras to detect and track objects. Real time feedback can be provided to the operator which enhances the safety during heavy equipment operation.

On a construction site, scaffolding is one of the major cause of injuries and accidents. Safety elements like toe-boards and guard-rails are installed to prevent from falling. (Q. Wang, 2019) proposes an automatic inspection technique to conform the safety regulations. After the location of vertical scaffolding is detected from point cloud data, planar surface is identified for platforms of the scaffolding. The four sides of the work platform give the toe-board and guard-rails. Safety regulation check i.e., the height of the toe-board, number, and location of guard-rails is applied on the extracted toe-board and guard-rails elements. The focus of (Q. Wang, 2019) for the scaffolding safety inspection is mostly on the toe-board and guard-rails, rather than the entire structure. (Rui et al., 2022) proposes a model for 3D deformation monitoring of scaffolding. Due to limited scanning range of LiDAR, (Rui et al., 2022) uses point cloud scanned by multiple stations called multi-thread LiDAR technology. The proposed model consists of point cloud alignment and tube axes modelling. The geometric relationship of the planar features in the scan is used to calculate the transformation parameters for point cloud alignment. For scaffolding tube axes modelling, (Rui et al., 2022) combines least-square method RANdom SAmple Consensus (RANSAC) algorithm. Deformation of scaffold is monitored by comparing tube axes model at different times. This approach of point cloud alignment requires sufficient planar surface in the scan. A 3D reconstruction model for monitoring scaffolding is proposed in (J. Kim et al., 2022), RandLA-Net a semantic segmentation method was implemented to identify scaffolding from a point cloud data collected using robotic dog. The deep learning model is trained both from scratch and through transfer learning with the Semantic3D dataset. 3D CAD model is generated from the predicted scaffolding point cloud. (J. Kim et al., 2022) was more focused on identification and 3D reconstruction of scaffolding on the site. On a large construction site, it is computationally inefficient to identifying small objects through direct processing of point cloud. (J. Kim et al., 2023) presents a methodology that integrates the benefits of 3D point cloud data and 2D image data to identify and locate the unsafe scaffold joints. 3D semantic segmentation was used to extract scaffolding from captured point cloud data. The scaffold joints were identified using coordinates of upright and guard rails and then joint image was generated. Deep learning model was trained to detect the ledger end and tail from the scaffold joint image which provides information about the safety status of the joint.

*Table 1: Previous studies on scaffolding inspection using point cloud data*

| Paper | Objective | Methodology | Data acquisition | Focus |
|---|---|---|---|---|
| Q. Wang, 2019 | Detection of toe-boards and guard rails | Using geometrical properties of point cloud data, the four sides of work | Terrestrial Laser Scanner | Toe-boards and guard rails |

| | | | | |
|---|---|---|---|---|
| | | platform was extracted after detecting the uprights (vertical) and platform (horizontal) | | |
| Rui et al., 2022 | Monitoring scaffoldings for deformations | Point cloud alignment and then comparing tube axis model for deformations | multi thread LiDAR | Planar surface for alignment |
| J. Kim et al., 2022 | Scaffolding extraction | 3D semantic segmentation model to identify scaffolding | Mobile Laser Scanner | Scaffolding identification |
| J. Kim et al., 2023 | Inspection of scaffold joints | Semantic segmentation to extract scaffolding and then point-to-image translation of joints for safety inspection | Terrestrial Laser Scanner | Scaffold joints |

To the best of our knowledge, there are limited research that combines scaffolding monitoring with point cloud data. (Rui et al., 2022) mentions lack of study utilizing point cloud data for temporary structure deformation. As illustrated in Table 1 , the research that incorporates point cloud data for scaffolding is either confined to specific parts of the scaffold or the identification of scaffolding. Based on the above table issues, the purpose of this work is to provide an approach to monitoring scaffolding structure for safety assessment and to develop a procedure for an efficient representation of scaffolding utilizing graph data structure.

## 3. METHODOLOGY

In this paper, the focus is on detecting the modification in the scaffolding during construction progress. As mentioned in section 1, the routine visual inspection of scaffolding is time-consuming and might be susceptible to errors due to human fatigue. During construction, there is a worker-structure interaction, i.e., for accessibility workers occasionally remove the components or braces of the scaffolding. The most common challenges encountered by the site manager during scaffolding inspection are that the elements of the structure are not placed back and even if they are placed, it has a chance of failure to adhere to the design rules. This could impact the structure's integrity and, eventually, the safety of the workers. The provided information is based on a semi-structured interview conducted with the site manager, whose one of the responsibilities is to ensure the safety of workers on a construction site.

This research tries to automate the routine inspection process and utilize the technology to assist the decision-making capability of the site managers. To monitor the health of scaffolding, this paper divides the overall inspection process into three parts: the initial or the baseline structure and campaign-based data acquisition, then performing a routine inspection for structure comparison and modification, and finally, representing the scaffolding using graph data structure. The overall process flow is given in Figure 1. Figure 2 adapted from (Karim et al., 2016) shows the comprehensive pipeline used in this paper, steps include data acquisition to knowledge extraction and ultimately leading to visualization. Domain knowledge from construction site is incorporated as a first step in the research pipeline, also verification of design rules adhered to during scaffolding installation could be performed to determine the structural integrity.

Various devices like Light Detection and Ranging (LiDAR) scanners and robotics platforms, including

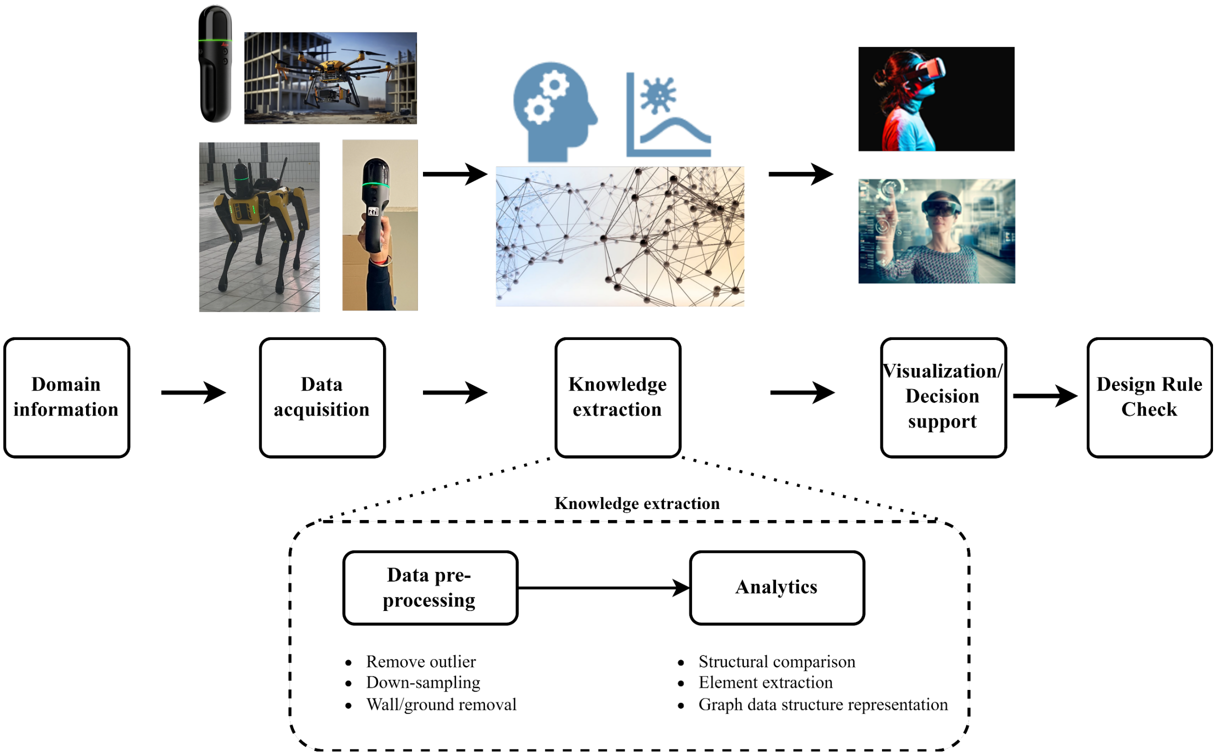



*Figure 2: Research pipeline*

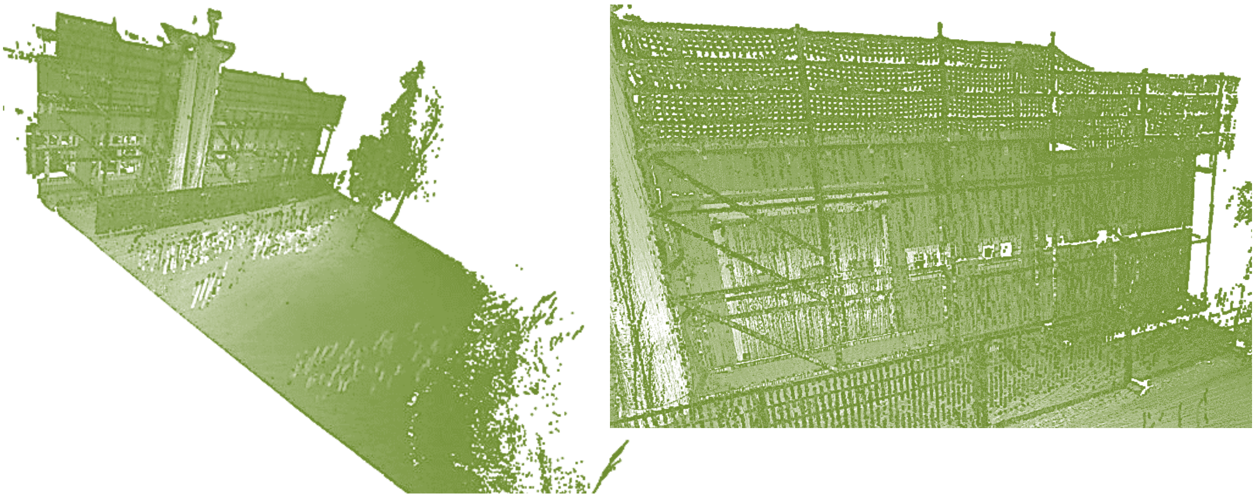
autonomous robot dog and drones are employed to collect raw 3D data. A LiDAR device sweeps laser across a wide area and collects millions of distance measurements to give 3D point cloud data. The acquired point cloud data represents the spatial attributes of the environment, offering extensive information which requires further processing. The knowledge extraction phase, as shown in Figure 2, involves various important operations such as data pre-processing, structural comparison, and graph data structure representation. By eliminating the outliers and extracting the object of interest, data cleaning and processing ensures that only high-quality information is retained. This extracted scaffolding from the raw data still contains substantial number of points that requires effective representation. The scaffolding can be defined as the interconnection of rods and joints and in this work, graph data structure is employed as an effective method to represent the scaffolding. This representation is well suited to capture the relationships between nodes (joints) and edges (rods). Furthermore, graph-based approaches can leverage well established methodologies in network analysis to gain deeper understanding of the scaffolding structure. The stability of scaffolding may be influenced by structural modifications that might occur during the construction phase. The processed and extracted scaffolding point cloud data is compared with the certified data of the original scaffolding design to identify the structural changes or deviations. Hence, the scaffolding needs to be monitored continuously and any alterations in the structure should be highlighted and reported. By direct attention towards these modified areas, the site manager can prioritize the inspections and ensure targeted corrective actions, optimizing both time and resource allocations. On this basis, the technology will assist the site manager making an informed decision on the health of the scaffolding and the safety of workers. Finally, the visualization stage uses advanced tools like Augmented Reality (AR) and Virtual Reality (VR) to visualize and take decisions on the extracted knowledge from the processed data. Different stakeholder can use this immersive visualization facilitates to intuitive interact with the data and to make informed decisions.

# 4. RESULTS

This section demonstrates the results achieved during different phase of research pipeline.

## 4.1 Data acquisition

The raw point cloud data of scaffolding from a construction site which is acquired using LiDAR device is shown in Figure 3. The figure shows different point of view of the acquired data. As shown in figure the raw 3D point cloud obtained from a construction site having 16 million points, which contains noise and other objects which are not of interest.



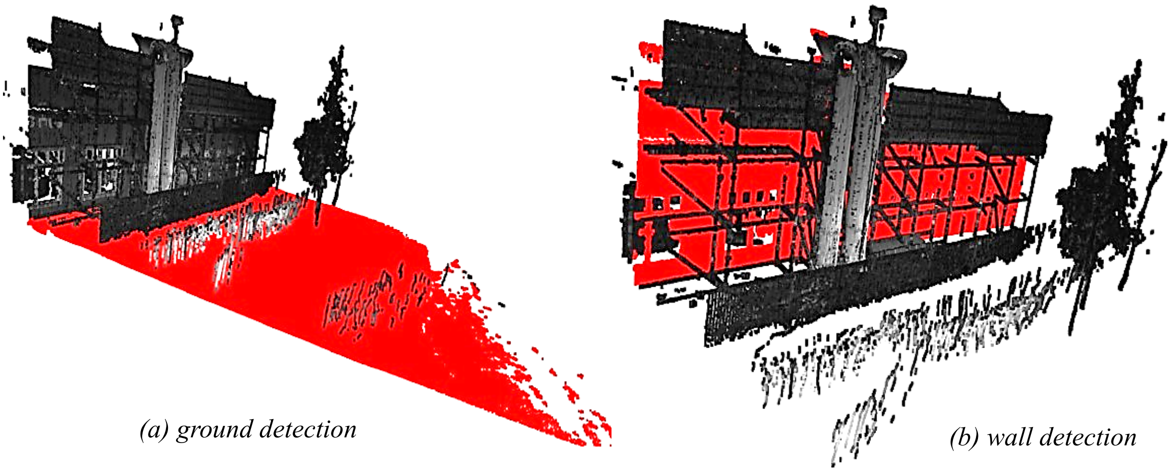
*(a) view 1*

*(b) view 2*

*Figure 3: Raw point cloud data of scaffolding*

## 4.2 Data pre-processing

The pre-processing step which is discussed in this section is common for the initial and periodic data acquisition. Raw data points contain noise, outliers, redundant points, therefore pre-processing steps is required to remove these imperfections and to make data accurate and reliable. To extract the object of interest, the pre-processing steps involve removal of ground plane, outlier removal, voxelization to reduce the number of data points and make the data manageable for further processing. In voxelization, point cloud data is converted into uniformly sized grid and points within each grid is aggregated. For planar surface removal, iterative algorithms like RANSAC (Rui et al., 2022) which identifies and separates the planar surface from the rest of the point cloud data is used. RANSAC works by repeatedly fitting planes on some random data points and selecting plane with most inliers. Through this, planar surface is identified and removal of which gives the object of interest which is scaffolding. Figure 4 shows the detected ground plane and wall in red colour. Scaffolding is erected at a certain distance from the wall. Once the wall is detected, all the data points beyond that distance can be eliminated, which give the object of interest as shown in Figure 5.



*(a) ground detection* *(b) wall detection*

*Figure 4: Processing of point cloud data*

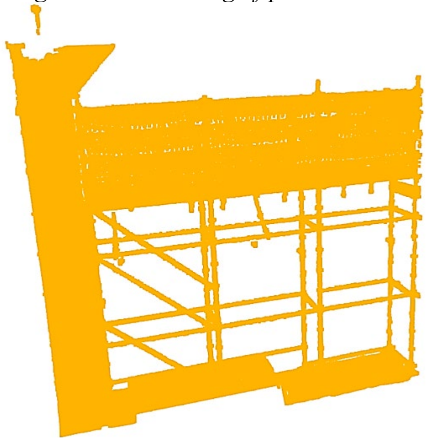


*Figure 5: Initial scaffolding point cloud data*

## 4.3 Structure comparison

This step is similar to site manager routine inspection where in every two weeks or as per the requirement, a LiDAR scan of the same construction site is carried out. For routine inspection, campaign-based LiDAR scan data is acquired, which is compared to the original scan data to identify modifications in the scaffolding structure. The pre-processing steps as mentioned in section 4.2 is performed on this new acquired point cloud data. The two major issues faced by the site manager during monitoring are missing and deviated elements of scaffolding. This happens as the construction progresses and workers for their ease of access modify the temporary structure, which is shown in Figure 6. The missing element is shown as a circle in red whereas the shifting and deviation of an element is shown by red arrows.

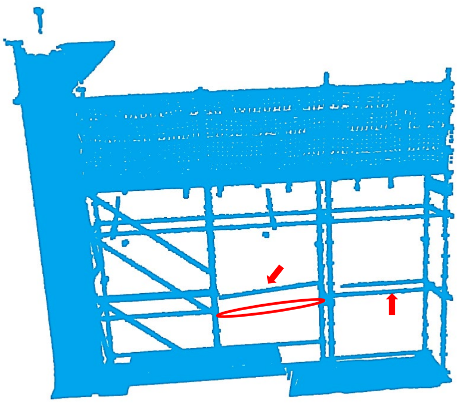


*Figure 6: Campaign based scan*

The recent clean extracted scaffolding is compared with the initial certified point cloud of scaffolding to identify any modifications made, so that the site manager put focus only on those particular sections. Iterative closest point algorithm (L. Li et al., 2021) is used to align and minimize the distance between the two point cloud data. This algorithm computes transformation matrix, a combination of rotation matrix, R and translation matrix T, so as to minimize the mean squared error. It is represented in equation below, where I is the data from initial certified scan and C is from current scan, $N_p$ denotes the total number of data points.

$$Error(R,T) = \frac{1}{N_p}\sum_{i=1}^{N_p}\|I_i - RC_i - T\|^2$$

For each point in C, the algorithm finds the closest point in I to create a point correspondence. Using these correspondences, the algorithm estimates the optimal transformation matrix that best align the two point cloud dataset. To check for convergence, the algorithm evaluates the change in error and iterate until convergence or the maximum number of iterations is reached. To visualize the alignment quality between the two point cloud dataset, the distance for each point data is computed. And then to distinguish between well-aligned and poorly aligned points a threshold to the maximum distance is set, the distance is colour-coded depending on the severity level. If the distance between current scan data points and certified scan data points are within the threshold, the points are coloured green. While those exciding the threshold are coloured red, highlighting possible misalignment and the site manager can inspect the highlighted section for a complex site.

Figure 7 shows the output from the algorithm. The points which are matching or identical between the two-point cloud scans is shown in blue colour whereas the modified points are highlighted in yellow. For a large complex construction site with scaffoldings at multiple locations, this gives the indication to the site manager to focus on certain areas which requires attention. The percentage of deviation or modification can be adjusted by tuning the threshold parameter in distance calculation between two-point cloud scan. The distance is calculated after overlapping the recent routine inspection scan with the initial certified scan. Depending on the level of severity of modifications, the threshold to the maximum distance is set, which is in the hands of site manager. Figure 8 shows the points having distance value less than the threshold in green whereas points with larger distance then threshold in red. Figure 8(a) is for 10% threshold when a small deviation is acceptable and will not affect the integrity of the structure whereas Figure 8(b) is where even a small deviation is unacceptable the threshold can be reduced to 5%.

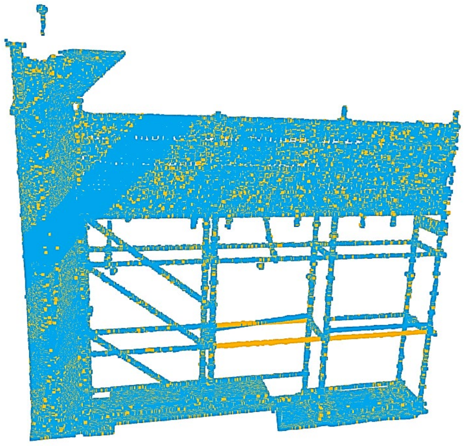
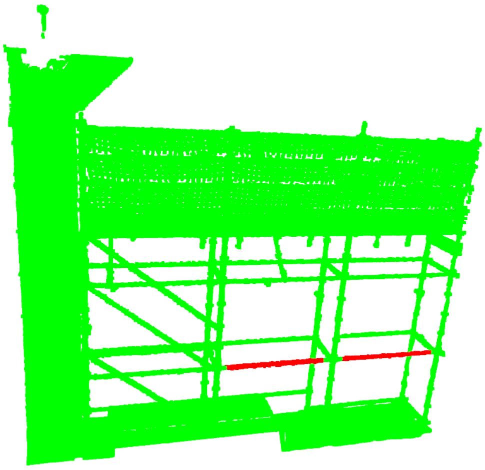
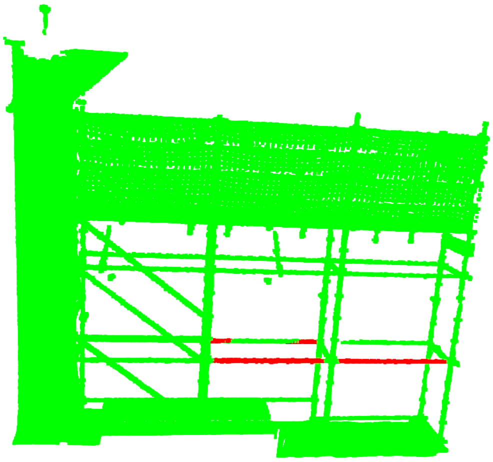


*Figure 7: Structure comparison*



*(a) 10% threshold*

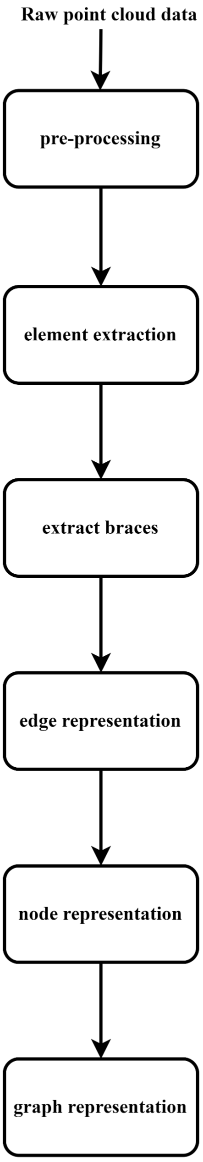


*(b)5% threshold*

*Figure 8: Distance comparison*

## 4.4 Graph representation

Scaffolding are structures composed of interconnected components such as tubes and joints which can naturally be modelled in a graph data structure with links and nodes. The graph structure consists of links, which represents the physical elements like rods or braces of scaffolding and nodes, which represent the joints or connection of braces. It is possible to represent a complex point cloud data of scaffolding in an efficient and systematic way by leveraging a graph data structure. Figure 9 shows the steps involved from scaffolding raw point cloud data to graph data structure representation. In the first step, the scaffolding is extracted from the raw point cloud data. To segment the point cloud data according to local shape characteristics, for each point the KDTree algorithm (Guo et al., 2017; Lin et al., 2020) is used to identify neighbouring points within a pre-defined radius. The principal components are computed using Singular Value Decomposition, which determines the shape descriptors such a linear, planar, and spherical. This provides a depiction of scaffolding based on different shapes, such as linear for braces, planar for platform and sheets, and spherical for joints. The result of this is shown in Figure 9 under element extraction, where braces are represented in green colour, joints in red whereas planar surface such as safety sheet in blue colour. The Density-Based Spatial Clustering of Applications with Noise (DBSCAN) (Ester et al., 1996; J. Kim et al., 2024) algorithm is implemented to cluster the point cloud data and subsequently extract the linear elements that correspond to the braces of the scaffolding. To reduce the data and computation complexity for each cluster, two farthest points and the alignment of the braces are computed. Next for each of the farthest points, their corresponding close data points are identified and the mean of all those points is computed, which represents a physical joint of a scaffold. As shown in figure, braces are represented in colour green, joints represented in red are the mean of the farthest points for every bounding box which are represented as dotted lines. This information



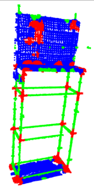
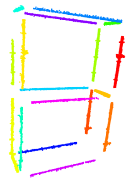
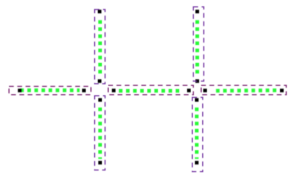
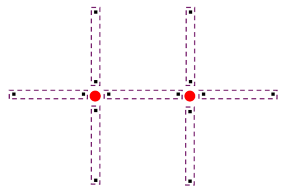
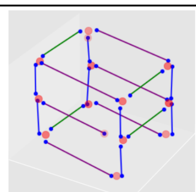
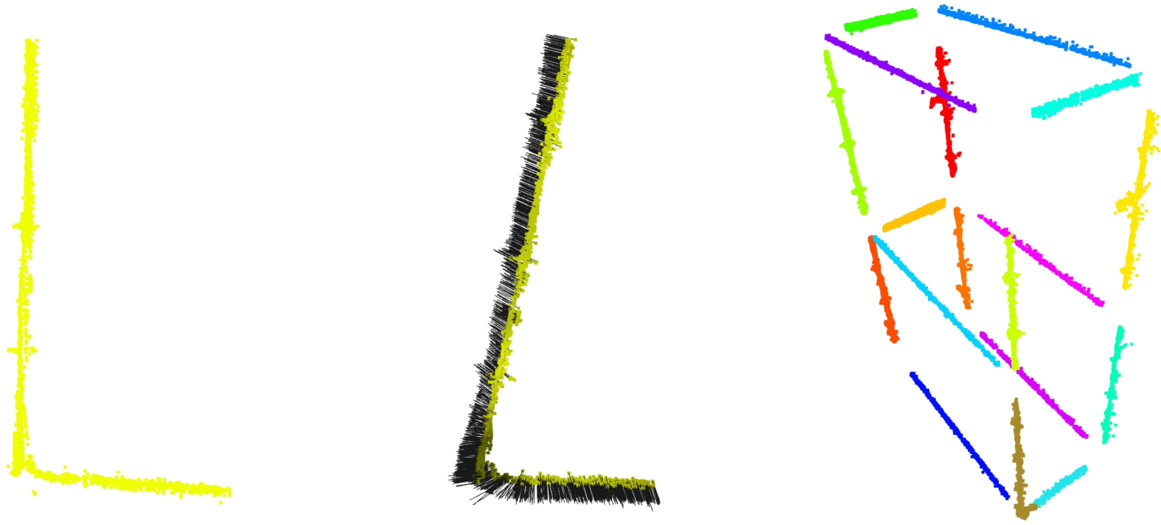

| Process | Outcome | Figure |
|---|---|---|
| • Voxelization<br>• RANSAC | • Reduce number of points<br>• Object of interest (scaffolding) |  |
| • KDTree<br>• PCA | • Linear element - braces<br>• Planar surface - sheets<br>• Spherical element - joints |  |
| • DBSCAN | • Clustering of braces<br>• Removing small clusters |  |
| • Bounding boxes<br>• Find two farthest points in each bounding box | • Two points for each brace<br>• Alignment of each brace |  |
| • For each farthest point find all the closest points<br>• Mean of all those points | • Joint between braces |  |
| • Mean value, brace alignment with connected nodes<br>• Color coding the x, y, z and diagonal oriented braces | • Reduce complexity<br>• Easier to handle |  |

*Figure 9: Steps involved for graph data structure representation*

detailing the farthest points and their alignment, as well as the information on the intersection helps in a graph data structure representation of a physical scaffolding. The colour coding for each brace in horizontal x direction, horizontal y direction and vertical direction of a scaffolding, represented as a graph data structure is presented in the last row of the figure.

### 4.4.1 Edge case

Element extraction step separates linear elements i.e., braces from spherical components like joints, followed by the application of DBSCAN algorithm to cluster the braces. However as shown in Figure 10(a), some clusters includes both vertical and horizontal braces as one label, which is regraded as an edge case in this paper. To address this, additional normal vector-based separation is implemented, targeting the wrongly or misclassified clustered elements. The normal vector for edge case is shown in Figure 10(b). Therefore, for edge cases two-fold clustering is employed, initially based on spatial distance and then based on normal-vector direction. As shown in Figure 10(c), the resulting labels generated from both the clustering approaches are merged, this ensures more accurate differentiation between vertical and horizontal braces of a scaffolding.



*(a) edge case* *(b) normal vector* *(c) two-fold clustering approach labels*

*Figure 10: Edge case clustering*

## 4.5 Visualization

As discussed previously one of the major issues identified during inspection is the missing element of scaffoldings. Figure 11 shows the graph representation of a scaffolding with highlighted missing element in red. The graph representation of the initial scan is compared with the recent scan when an element is missing, and the resultant representation is shown in Figure 11.

Virtual Reality (VR) and Augmented Reality (AR) are transformative technologies that are changing construction industry through better visualization capabilities (X. Li et al., 2018). VR creates an experience by immersing users in a fully simulated environment, effectively blocking out the physical world. This allows users to interact and navigate virtual environments in a manner that closely resembles reality, providing an engaging experience. On the other hand, AR superimposes digital information onto the real physical world, enhancing the user's interaction with their surroundings. With the use of these tools, site manager can virtually walk through to perform inspection of the scaffolding and specifically target the areas which requires attention to ensure the integrity of the structure. A screenshot from the AR glasses is shown in Figure 12, where the red colour represents missing element and yellow colour represents a deviated element of the scaffolding. These technologies break down the geographical barriers, raising the bar for collaboration practices by diving into 3D models and perform hands-on that goes beyond computer screens. This promotes real-time discussions, solution to problems and coordination, resulting in improved decision-making.

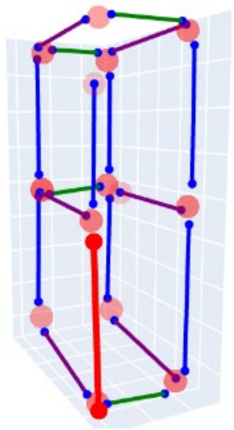


*Figure 12: Graph representation comparison*

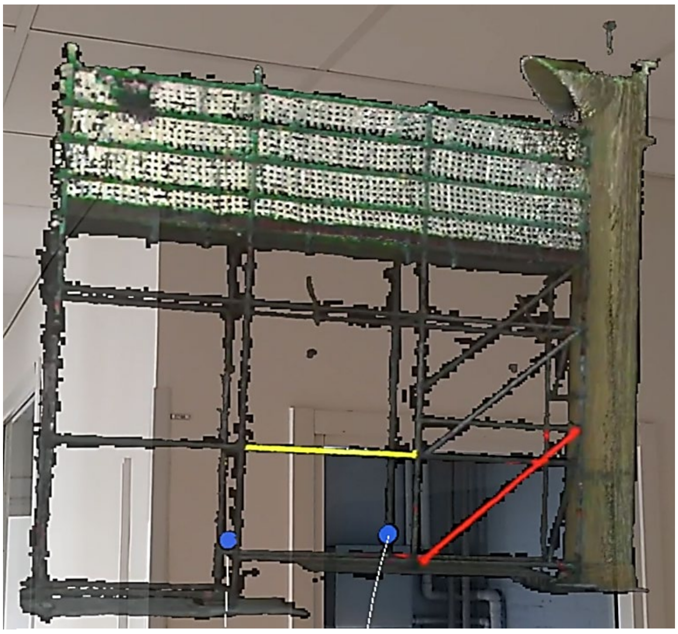


*Figure 11: AR view for site manager*

## 5. CONCLUSION AND FUTURE WORK

This paper presents a robust method to automate the routine inspection of the scaffolding on a construction site. By comparing the point cloud data of original and certified scaffolding with the recent scan on a regular interval, deviations or missing elements of a scaffolding can be detected. This automation in monitoring the scaffolding on a complex construction site will reduce the time and effort required by the site manager. This paper also suggests an efficient way to represent the scaffolding using a graph data structure, which can integrate numerous well-established graph algorithms, making the approach versatile for advance analysis. The section or the component of scaffolding that is modified during construction progress is highlighted and the site manager can focus on that particular section, which reduces inspection errors due to human fatigue. Incorporating advance tools like VR/AR for visualization not only enables remote visualization but also foster real-time discussion and coordination for better decision-support. The proposed approach is one of the ways to enhance the safety of the workers and people on and around the scaffolding by minimizing the errors associated with visual inspection.

To increase the safety on a construction site, early signs of wear, damage or unauthorized changes needs to be identified. This work aligns with PHM concepts by providing continuous monitoring of scaffolding to track changes or modifications in the structure. By regularly monitoring the scaffolding to detect for unwanted modifications helps in predicting potential failures or safety hazards. Continuous monitoring the health of scaffolding also assists in forecasting when the elements may need maintenance, thus improving the safety.

When the scaffoldings are installed or erected, adherence to design rules ensure the stability and safety. This work establishes the foundation for future advances in condition monitoring of scaffolding. Among the possible extensions, one can be the integration of design rule verification, which would enable the system to automatically evaluate the current condition of the scaffolding against predetermined design specifications. A more autonomous decision support system can be developed by implementing an expert system framework. This paper proposed a way to model and represent the scaffolding using graph data structure.

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