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Towards Governed Human–Automation Collaboration for Decision-Making in Construction Project Management: A Practitioner's Perspective

Yiping Li [1], Liupengfei Wu [2], Frank Ghansah [3] and Hao Chen [4,*]

[1] School of Intelligent Accounting, Zhengzhou Vocational College of Finance and Taxation, Zhengzhou 450048, China; yipingli@yeah.net
[2] Division of Industrial Data Science, School of Data Science, Lingnan University, Hong Kong SAR, China; mikewu@ln.edu.hk
[3] School of Construction, Property and Surveying, College of Technology and Environment, London South Bank University, London SE1 0AA, UK; frank.ghansah@lsbu.ac.uk
[4] Department of Civil Engineering, American University of Sharjah, Sharjah 26666, United Arab Emirates
* Correspondence: hchen@aus.edu

Abstract

Construction automation is advancing rapidly, yet its integration into project-management decisions raises questions about organisational readiness, accountability and reliance on machine outputs. Existing studies largely emphasise technical capability or adoption intention, offering limited practitioner evidence on how decision authority is allocated in project settings. This study analyses semi-structured interviews with 13 Hong Kong construction practitioners conducted between March and December 2021. The interviews elicited perceptions of machine intelligence and associated digital decision support, which are interpreted within a broader human–automation collaboration framework. Participants described cost and learning requirements, implementation motivation, technical staffing and digital leadership as adoption concerns. They also linked the perceived role of automation to task context, input quality, familiarity, organisational culture and accountability. Their implementation suggestions emphasised needs-driven selection, bottom-up participation and complementary technology support. The resulting conceptual framework connects readiness, role allocation, accountability and feedback learning. It proposes explicit decision ownership, override and monitoring arrangements for project-management applications.

Keywords: human–automation collaboration; construction automation; project management; decision authority; technology adoption; qualitative interviews

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1. Introduction

The construction sector is a major contributor to economic activity and social development. In many countries, it accounts for approximately 5–7% of gross domestic product (GDP) [1]. Research and development (R&D) therefore seeks to improve productivity and competitiveness while strengthening worker health and safety [2]. These objectives remain difficult to achieve because construction is labour-intensive, its workforce is ageing, and persistent safety and productivity problems continue to affect project delivery [3]. Compared with sectors such as manufacturing, construction has also been slower to adopt technological innovation and advance digital transformation [4]. Industry 4.0 technologies, including cyber–physical systems, artificial intelligence (AI), automation and robotics, create opportunities to shift selected activities from labour-intensive execution towards

digitally enabled delivery. The Construction 4.0 framework brings these technologies together across industrialised construction, cyber–physical systems and related innovations to improve project performance [5–7]. For example, sensing-technology-enabled methods have been developed to assess carbon mitigation ambitious from construction waste on site [8]. These developments suggest that future project delivery will increasingly combine practitioner expertise with automation. The relevant management question is therefore not whether technology will enter projects, but how it should be selected, governed and incorporated into decisions affecting cost, time, quality, safety and operational performance.

As technical development accelerates, the social and organisational integration of construction automation has attracted increasing attention [9,10]. Automation is progressively entering professional decision processes, where it can provide evidence, recommendations or bounded actions rather than merely executing predefined tasks [11]. AI supports classification and prediction [12], while blockchain and IoT have been combined to support information exchange in prefabricated housing [13]. These capabilities do not themselves determine whether system outputs should govern project decisions [14]. This has prompted expectations that future work will increasingly involve human–machine collaboration [15]. Research on managers' attitudes and behavioural intentions examines their willingness to use AI in organisational decisions [16]. In this study, human intelligence (HI) denotes practitioners' capacity for contextual interpretation, learning, reasoning and accountable judgement. These capabilities remain subject to bounded rationality, particularly when decisions involve time pressure, incomplete information and substantial cognitive demands [17]. The complexity and data intensity of construction projects can therefore exceed unaided human processing capacity. Machine intelligence (MI) can complement HI by supplying consistent computation and pattern recognition [18]. MI is defined here as a value-adding system that uses adaptive algorithms to reproduce selected cognitive functions, including learning, prediction and decision support. Construction has long used MI-enabled applications, such as computer-vision safety monitoring and cyber–physical system monitoring, as tools [5]. More recent applications, however, position MI as a potential collaborator within the decision loop. Practitioners' willingness to grant this role depends on their acceptance of, and trust in, the system [19]. Strong machine capability may encourage over-reliance and reduce critical monitoring—a form of algorithm appreciation [20]. Conversely, distrust can produce algorithm aversion and rejection of useful machine input. The relevant roles are therefore better represented as human-led decisions, decision support and bounded machine action. Understanding how practitioners calibrate these roles is essential to construction project management because decision authority and accountability cannot be inferred from technical capability alone.

Research on construction automation has concentrated on technical performance and adoption antecedents, but offers limited practitioner evidence on (1) how automation should enter project-management decision loops, (2) how decision authority should be allocated, and (3) what organisational conditions sustain responsible use. Addressing these gaps, this study examines three connected issues: adoption readiness, role calibration within project decisions, and implementation arrangements for wider diffusion. Its contribution is threefold. First, it links adoption readiness to decision authority instead of treating adoption and use as separate problems. Second, it identifies task context, familiarity, culture, input quality and accountability as conditions governing the legitimate role of automation. Third, it translates the interview themes into a multilevel governance framework for construction project management. Because the evidence is qualitative and specific to Hong Kong, the framework is explanatory rather than statistically representative.

2. Literature Review

2.1. Construction Automation

Construction combines high labour intensity, project-based production and comparatively slow technology adoption, contributing to persistent safety, efficiency and productivity problems [21]. Alongside management and process improvement, automation offers a means of transferring selected tasks from manual execution to technology-enabled delivery [22]. Definitions of construction automation vary. For example, Skibniewski [23] described construction automation as the engineering discipline that automates selected processes through teleoperated, numerically controlled, semi-automatic or automatic equipment. From a benefits perspective, Castro-Lacouture [21] defined it as the use of equipment and control techniques to reduce labour demand, increase productivity and improve worker health and safety. In this study, construction automation refers broadly to technologies with varying degrees of autonomy that execute or support construction work and project-management decisions. Machine intelligence is used more narrowly for systems with adaptive or analytical decision capability. This distinction also bounds the empirical claims: the interview guide elicited views of machine intelligence (Appendix A), while automation provides the broader lens used to organise those accounts. The interviews therefore do not represent the full range of construction automation, particularly for systems without an analytical or decision-support function.

Construction automation can be applied across multiple project lifecycle stages. For example, Son et al. [24] categorised applications into planning and design, construction robotics, intelligent job-site management, operation and maintenance, and other areas. Alternatively, Castro-Lacouture [21] classified applications from a construction-management perspective into planning and scheduling (e.g., BIM and CAD), cost management, and performance management (e.g., RFID, laser scanning and vision tracking). Construction 4.0 extends this lifecycle perspective by integrating technologies across project stages to improve the efficiency, accuracy and timeliness of information and action [5]. BIM, unmanned aerial systems, and AI continue to expand the range of available project applications [25–27]. Their managerial value, however, depends on whether project organisations can translate technical capability into operationally appropriate routines and decisions [5].

Despite their potential to improve project performance, construction-automation applications continue to face substantial adoption barriers [28]. Reported uptake remains below expectations [2]. Nagy et al. [29] identified six organisational-level challenge groups: human resources and societal factors, organisational conditions, management readiness, market promotion, investment and return, and user satisfaction. Similarly, Osunsanmi, Aigbavboa, Emmanuel Oke and Liphadzi [28] surveyed 91 practitioners and found that willingness to adopt Construction 4.0 technologies coexisted with limited awareness of their practical value. Financial constraints, insufficient technological understanding and the project-based nature of construction were among the most influential barriers. These findings indicate that adoption is not a one-off procurement decision; it is an organisational-change and project-governance process requiring coordinated resources, capability development and implementation oversight.

2.2. Automation-Supported Decision-Making in Construction Project Management

Dual-process theory distinguishes intuitive, rapid judgement (System 1) from slower, deliberative reasoning (System 2) [30], and suggests that people often rely on System 1 when time and cognitive resources are constrained. System 2 can correct intuitive judgement but requires attention and working memory [31]. Even deliberative decisions remain bounded by incomplete information and limited cognition [32,33]. Under task complexity and time pressure, decision-makers may therefore select satisfactory rather than fully optimised

alternatives [34,35]. Decision intelligence introduces computational support to extend, rather than eliminate, human judgement [36].

Construction project decisions are increasingly supported or partially automated by digital technologies [22]. For example, BIM-enabled robotic systems can identify materials, detect defects and generate status reports for site inspections [37]. BIM-based generative design can support sustainable offsite construction [38]. BIM-based systems can also plan concrete formwork demand and potential reuse [39]. These applications differ in how much authority they exercise. As technology becomes capable of handling tasks that once required human sensing or cognition, it may advise a decision-maker or perform a bounded decision autonomously [40]. Yet decision aids are not adopted simply because they are technically capable. Haesevoets, De Cremer, Dierckx and Van Hiel [15] found that managers often discounted machine advice, a pattern described as algorithm aversion. Fear of replacement, system imperfection, false expectations, limited control and weak incentives can all contribute to this response [14]. Mahmud et al. [41] showed that algorithm aversion arises from interacting algorithm, individual, task and contextual factors. At the opposite extreme, algorithm appreciation can lead users to rely on machine advice more heavily than on their own knowledge [20]. When users trust automated advice, a system may be assigned a supportive or replacement role [42]. Algorithm aversion and appreciation describe reliance; they do not, by themselves, determine legitimate authority. This study therefore distinguishes human-led decisions, decision support and bounded machine action. The project-management problem is to determine which role is defensible for a particular decision, project stage and risk profile.

3. Methodology

3.1. Semi-Structured Interview Design

Figure 1 links the industry background to the study questions and empirical workflow. The historical McKinsey digitisation index [43] provides historical context for uneven digitalisation across sectors; it is not an output of the interviews. Semi-structured interviews were selected to examine practitioners' accounts of adoption, decision roles and implementation. The guide used "machine intelligence" (MI), with questions about experience, system characteristics, collaboration, perceived roles and attitudes (Appendix A). These topics underpin the three analytical domains reported as adoption, in-loop use and diffusion. Construction automation is the broader interpretive frame used to organise these accounts. This mapping does not imply that all BIM tools are intelligent or autonomous, or that every type of automated construction system was covered. The guide retains its original MI terminology so that the scope of the elicited construct remains explicit.

3.2. Participant Recruitment

Participant recruitment adopted a purposive sampling strategy to identify practitioners with relevant experience in construction digitalisation, automation, and technology-supported project decision-making. Eligible participants were required to: (1) be currently working, or have recent professional experience, in Hong Kong's construction industry; (2) have direct experience with digital construction, automation, BIM, AI, or related technology-enabled project processes; and (3) have sufficient professional experience to provide informed views on technology adoption, implementation, or decision-making. Participants were approached through the industrial partner, LinkedIn and referrals. Recruitment continued until the research team considered that the interviews provided sufficient coverage of the main issues relevant to the study objectives. The sampling was intended to obtain informed, practice-based accounts rather than statistically represent the wider construction workforce. The final sample comprised 13 participants with experience relevant to technol-

ogy adoption, automation-supported decisions and implementation conditions. Table 1 summarises the participants' professional roles, organisation types and digital experience. Industry experience ranged from 7 to 20 years, and reported technologies included BIM, automation, digital coordination and modular integrated construction (MiC). Organisation size and project sector are not reported in the available participant profile; the analysis therefore does not compare adoption across firm-size, ownership or project-sector groups.

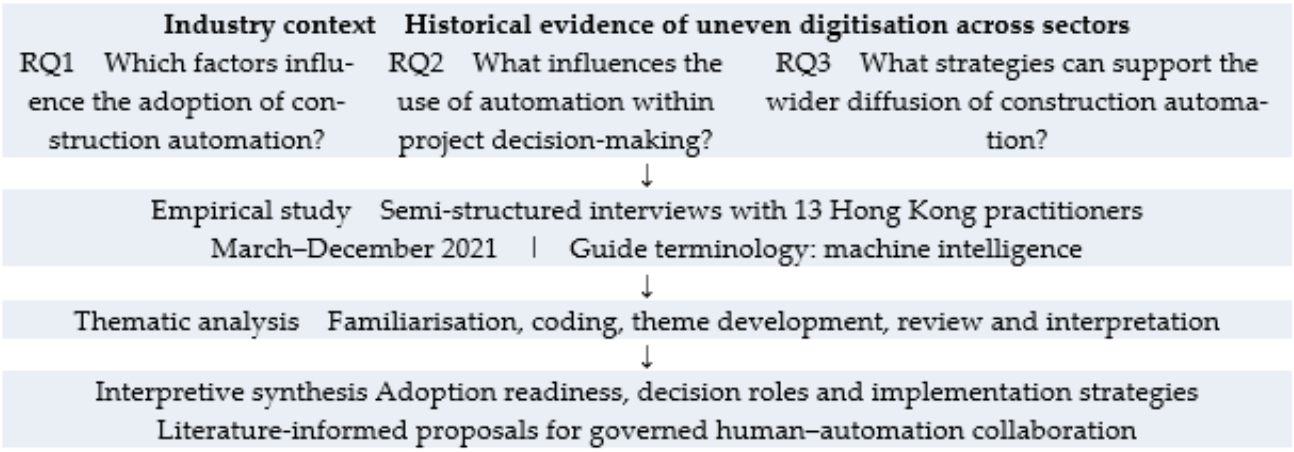


Figure 1. Research questions and methodological workflow developed by the authors. The industry background is informed by the historical McKinsey digitisation index [43] (2015 or latest available data, published in 2016).

Table 1. Professional profile of interview participants.

Participants	Professional Role	Industry Experience (Years)	Organisation Type	Digital/Automation Experience
P1	Project Manager	15	Main contractor	BIM; digital coordination
P2	BIM Manager	12	Main contractor	BIM implementation; CDE
P3	Designer	9	Engineering consultant	BIM; digital design
P4	Designer	14	Consultant	BIM; automated analysis
P5	Construction Manager	18	Main contractor	Digital site management
P6	Project Engineer	8	Main contractor	Automation and BIM
P7	BIM Manager	16	Contractor	Automation; data analytics
P8	BIM Manager	7	Consultant	BIM; model checking; system calibration
P9	Quantity Surveyor	11	Cost consultant	Digital cost management; BIM
P10	Project Manager	20	Client/developer	BIM-supported decision-making
P11	Structural Engineer	13	Engineering consultant	Automated modelling and structural assessment
P12	Senior manager	17	Main contractor	MiC; BIM; logistics; construction technology
P13	Senior manager	15	Contractor	Automation strategy; BIM; digital transformation

The interviews were conducted between March and December 2021 and lasted approximately 50 min each. Interviews were conducted in person in English, Cantonese or Mandarin. With participants' consent, all interviews were audio-recorded and subsequently transcribed verbatim for analysis. Where interviews were conducted in a language other than English, relevant quotations were translated into English during preparation of the manuscript. To improve transparency and reproducibility, the semi-structured interview guide used to structure the interviews is provided in Appendix A. These accounts predate widespread deployment of large language models. The later literature is used to contextualise the interpretation rather than to attribute contemporary generative-AI experience to the interviewees.

3.3. Thematic Analysis

The interview transcripts were analysed using thematic analysis following the six-phase procedure proposed by Clarke and Braun [44]: (1) familiarisation with the data, (2) generation of initial codes, (3) searching for candidate themes, (4) reviewing themes against the coded extracts and the full dataset, (5) defining and naming themes, and (6) producing the final analysis. Two researchers participated in the coding process. Differences in interpretation were discussed until agreement was reached. A codebook was maintained throughout the analysis to record code definitions, inclusion and exclusion criteria, and changes made during theme development. The codebook was iteratively refined as coding progressed. Formal thematic saturation was not used as a predetermined stopping criterion for recruitment. The study adopted a purposive, exploratory design aimed at obtaining information-rich accounts from practitioners. Recruitment therefore focused on obtaining sufficient thematic coverage of automation adoption, in-loop decision-making and implementation conditions. As the later interviews increasingly reinforced themes already identified in the dataset and produced limited additional conceptual categories, the research team considered the sample sufficient for the analytical objectives of the study.

Figure 2 makes the evidence chain explicit by showing how interview material was synthesised into the three result domains—adoption, in-loop use and dissemination—and then translated into practice-oriented design guidance.

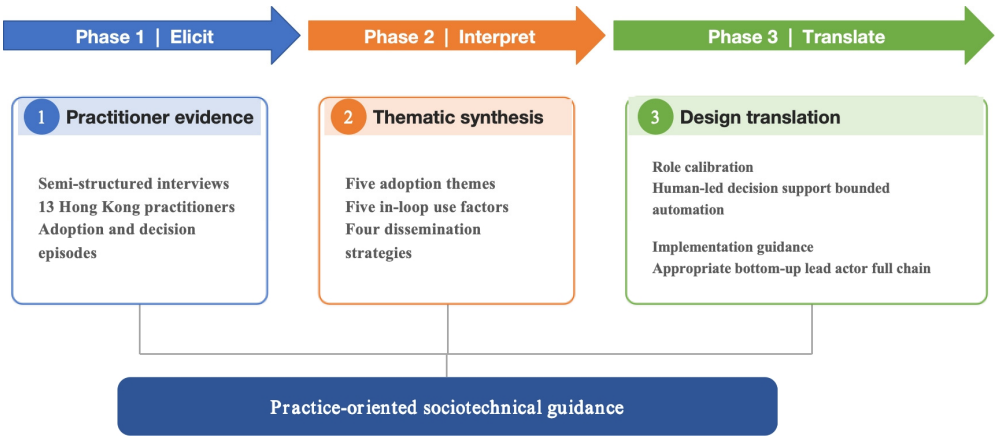


Figure 2. Qualitative evidence-to-design pathway used in this study.

The analytical pathway distinguishes evidence elicitation, thematic interpretation and design translation. Themes were organised around the research questions and compared with the concepts identified in the literature review. Table 2 links each question to its analytic domain, data route, reported themes, participant anchors and Section 4. The matrix supports traceability rather than quantification: theme order does not denote frequency

or importance, and participant identifiers locate evidence rather than provide respondent counts. All 13 interview transcripts were included in the thematic analysis and contributed to the development and refinement of the reported themes. The participant identifiers reported in Table 2 and Section 4 indicate the sources of illustrative verbatim quotations rather than the complete set of participants contributing to each theme. In particular, the interviews with P3, P5 and P9 informed the coding and interpretation of the thematic structure, although their statements were not selected as direct quotations because they primarily reinforced themes that were more clearly articulated by other participants.

Table 2. Research-question-analysis traceability matrix.

Research Question	Analytic Domain	Data and Analytic Route	Reported Themes and Explicit Participant Anchors	Results
RQ1. Which factors influence the adoption of construction automation?	Adoption antecedents and barriers.	Semi-structured interviews with 13 Hong Kong practitioners; thematic analysis; interpretive comparison with the prior literature.	Cost and learning; over-reliance risk; technical manpower; active motivation; digital leadership. Illustrative quotations: P1, P2, P6, P10.	Section 4.1
RQ2. What influences the use of automation within project decision-making?	Context, readiness, reliance, responsibility, culture and decision authority.	Semi-structured interviews with 13 Hong Kong practitioners; thematic analysis; interpretive comparison with the prior literature.	Situational factors; human–machine responsibility; adaptation and familiarity; culture; role of automation. Illustrative quotations: P1, P4, P6, P7, P8, P10, P11.	Section 4.2
RQ3. What strategies can support the wider diffusion of construction automation?	Needs-driven implementation and multilevel diffusion.	Semi-structured interviews with 13 Hong Kong practitioners; thematic analysis; interpretive comparison with the prior literature.	Appropriate automation; bottom-up promotion; government or leading-company leadership; full-chain technology support. Illustrative quotations: P12 and P13.	Section 4.3

Note: All 13 interviews were included in the thematic analysis. Participant identifiers indicate illustrative quotations presented in the Section 4 and should not be interpreted as the complete evidential base for each theme.

4. Results

4.1. Conditions Shaping Construction-Automation Adoption

The five adoption themes below were developed from coding across the full set of interviews. Quotations from P1, P2, P6 and P10 illustrate the reported concerns; these identifiers do not denote the complete set of participants contributing to each theme or establish theme prevalence. Other interviews, including those with P3, P5 and P9, contributed to thematic interpretation but are not quoted verbatim in this section.

4.1.1. Cost and Learning Requirements

Financial outlay and learning time were the first adoption concerns. P6 stated: "I think the most important factors to use automation is the money cost, and the learning process,

because you have to spend a lot of money and time to introduce automation in company. Therefore, many practitioners prefer to use traditional way." This account links adoption to upfront expenditure and the time required to establish new work practices. Chen et al. [45] identified related financial constraints, including initial capital requirements, uncertain returns and limited financing options. These conditions can make established methods appear less risky than an untested automation investment.

Learning requirements extended beyond initial tool training. Prior research has questioned whether education and training in the AEC sector adequately support digital work [2]. Studies of adoption in residential construction [46] and rural labourers' status in the construction workforce [47] place these learning needs within specific project and employment settings. Effective upskilling therefore requires more than a compliance exercise; it requires coordinated support from public bodies, industry leaders and organisational management [48].

4.1.2. Risks of Over-Reliance on Automation

A second concern in the 2021 interviews was over-reliance on automation. Later studies discuss related risks in generative-AI-supported academic work [49], autonomous vehicles [50] and human–robot collaboration [51]. These later examples provide context; they do not show that the participants had experience with contemporary generative AI. P6 described reliance on the automation systems known at the time: "My great concern is the human rely too much on the automation system. Because the current automation system is not mature. If human rely too much on automation, there will be an accident if the automation accidentally failures."

Over-reliance generally combines unwarranted confidence in system capability with a loss of vigilance in monitoring system performance [52]. It has been linked to automation bias [53], misuse, disuse and overtrust [54]. In AEC, digital transformation is still evolving and appropriate reliance has become a central human–technology interaction problem [54,55]. The interview evidence supports context-dependent reliance in which practitioners use automated outputs but retain the capacity to intervene when anomalies arise [51]. This balance is better understood as trust calibration: reliance should change with evidence about system capability and operating conditions [56].

4.1.3. Shortage of Technical Personnel

A shortage of specialised personnel was another adoption concern. P2 observed: "Even though our company have more than 100 BIM staff, but we still not fully satisfy our demand for BIM modeler." The statement describes an unmet need for specialised skills within P2's organisation. At the industry level, labour supply is affected by safety conditions, the labour-intensive nature of work and limited entry by younger workers [57]. An ageing workforce may further constrain sustained digital transformation [57]. Consistent with this concern, Fortune et al. [58] argued that skilled personnel are necessary for productivity improvement. The evidence therefore identifies technical staffing as an implementation capacity, not simply as a background labour-market condition.

4.1.4. Weak Implementation Motivation

Participants also questioned whether adoption was motivated by operational value. P2 observed: "This is actually a problem in whole HK. Although most of the company say they are full BIM, it is actually not, they do so because they are trying to attract people from other company by using those high-tech advertising." The account describes symbolic adoption, in which technology is used to signal modernity rather than to solve a defined work problem. A related explanation is the gap between environment policy promotion

and implementation [59]. Although public bodies and industry associations promote new technologies, firms may perceive limited implementation support and training [60]. Investment in technology, recruitment and retraining also creates organisational-change costs [29].

P2 perceived differences in implementation priorities across organisations and projects: "In addition, the big company or public government project is willing to use those new technology. However, small company and private sector concerns more on bidding the project." This is an individual perception, not a comparison established by the sample. Table 1 does not report the organisation size or project sector, and organisation type does not establish ownership. Research specifically addressing construction SMEs [61] provides external context for resource constraints, but does not supply missing characteristics of this sample.

4.1.5. Insufficient Digital Leadership

Digital leadership was the fifth readiness condition. It refers to technology-mediated social influence that changes attitudes, behaviour and performance at individual, group and organisational levels [62]. P2 described uneven willingness and familiarity across consultants: "However, some of the consultant are not willing to use this system even though we are paying for that. They think their own way is more easy for them, especially for old guys. They are not familiar with the mobile phone because actually when you using this kind of system meaning you need to know something. For the young guy, they are very familiar with technology, but for the old guys it is quite difficult." In addition, P1 also mentioned that "Management support is important because adopting a new system requires time, training and additional staff. If the company only asks employees to use the technology without providing these resources, people will resist it". This statement is also partially supported by P10 "The technology itself is not the main problem. If the management does not push it and make it part of the normal workflow, people will continue using the old method". This account points to differences in experience and support; it should not be read as evidence that age alone determines technology acceptance.

The prior literature likewise treats digital leadership as a condition of technology adoption. For example, Yang et al. [63] proposed four construction-leadership domains: cognitive, business, strategic and interpersonal. Zulu and Khosrowshahi [64] developed a taxonomy ranging from proactive and supportive to cautious, resistant and uncoordinated leadership. Together with the interview accounts, these studies draw attention to how leadership support is communicated, resourced and incorporated into work routines. Li et al. [65] examined AI and innovation ambidexterity in advanced manufacturing through knowledge search, absorption and integration. Their study provides a cross-sector comparison for the need to develop organisational knowledge capacity alongside access to technology; it does not establish adoption effects in the present construction sample.

Figure 3 brings the five adoption themes together as an interpretive readiness configuration: economic feasibility, technical capacity, appropriate reliance, implementation motivation and digital leadership. The connections represent the authors' synthesis of concerns that appeared across the interviews, rather than tested dependencies or necessary conditions. For project management, the synthesis suggests assessing these concerns together before incorporating a system into a workflow, instead of treating procurement as sufficient preparation for use.

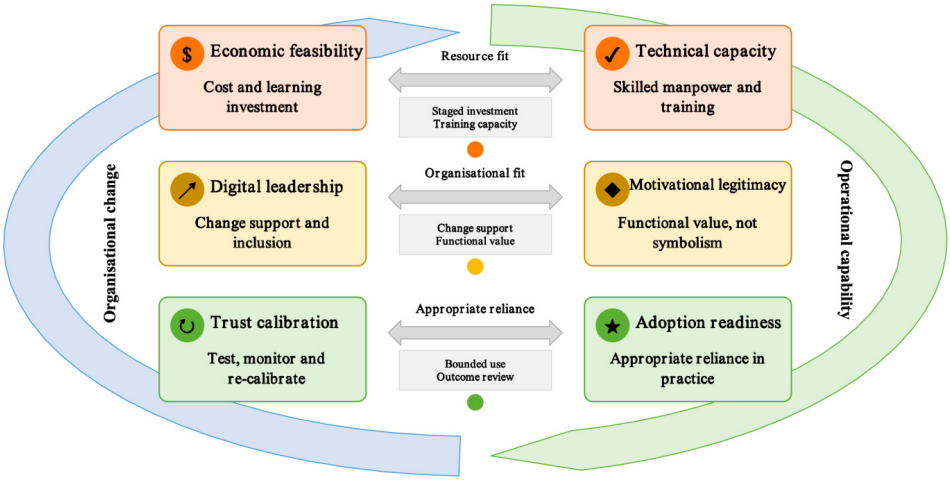


Figure 3. The interdependent conditions shaping automation-adoption readiness.

4.2. Conditions Shaping Automation's Role in Project Decision-Making

4.2.1. Situational and Task Factors

As automation enters decision-making, technical capability alone does not determine whether a system should receive authority [12]. The managerial problem is to identify the conditions under which automation can inform, recommend or undertake a bounded action [66].

Situational and task characteristics were prominent in participants' accounts. When discussing automated assessment of scaffolding, P11 observed: "They cannot ensure whether it is stable or safe because they cannot check every element of the bamboos. But for metals scaffold, they use automated model the PCs software to do that." The contrast between bamboo and metal scaffolding indicates that material properties and inspectability affect whether an automated model is considered credible. Project stage and decision consequence also shaped the perceived role of automation. P10 stated: "So if you, if someone talk about using BIM for make the decision for the critical issues, I think it wouldn't, it won't happen. And that actual situation, you know. So for BIM process, usually in the tiny stage, or in the decision stage, or in before the any actual works." The account suggests that practitioners are more willing to use automation in preparatory or lower-consequence settings than in critical decisions. Situational factors refer to the characteristics of the work setting or problem confronting a manager [67]. This contingency is consistent with evidence from automated driving, where Stoll et al. [68] found that criticality changes cooperative behaviour. In construction projects, role allocation should therefore be calibrated to task structure, project stage, reversibility and consequence severity. Hu et al. [69] illustrate structured scheduling support by integrating capacity planning, resource transfers and idleness in multi-project optimisation. Peng et al. [70] address constrained task allocation in post-disaster edge-computing systems using a fairness-aware learning algorithm. These technical studies make the importance of explicit objectives and resource constraints concrete, while leaving the separate managerial question of who may accept or override a recommended allocation.

4.2.2. Human–Machine Responsibility and Accountability

Responsibility attribution was a second condition shaping automation's role [71]. Tsumura and Yamada [72] experimentally examined how prior knowledge of an AI agent and task importance affect responsibility attribution following failure. This provides external context for the distinction between reliance and responsibility; it does not measure responsibility allocation in construction projects. P10 stated: "Even though we have fancy

model, it is the people that put the buttons on it," locating ultimate accountability with the human decision-maker. P6 raised a related concern: "My another concern is the accident responsibility, it is easy to tell for human-human, but it is unclear for human-automation collaboration. I like the automation, but they will only used as tool, not decision-making tools. In my view, the perfect AI should be simple to use and learn for construction workers." These accounts distinguish analytical assistance from accountability for the resulting action. This interpretation is consistent with Schoenherr and Thomson [71], who found that responsibility may be attributed differently to an AI system and its human operator. The project-management implication is that every automated use case requires an identifiable decision owner, escalation rule and override condition; responsibility cannot be assigned after failure occurs.

4.2.3. Adaptation to and Familiarity with Automation Technology

Participants also associated familiarity with their willingness to rely on technology. P8 stated: "I trust my machine 100% if you give me enough time to test and calibration? (Calibration of programs)." The quotation indicates that confidence was conditional on testing and calibration rather than unconditional trust. Prior studies likewise suggest that training and domain knowledge improve understanding of system behaviour [73,74]. Familiarity should therefore support calibrated reliance: users need sufficient knowledge to recognise both valid outputs and conditions that require intervention.

Gomez et al. [75] examine how collaborative user involvement can address knowledge imbalance in AI-advised decisions. Ciofu et al. [73] map the literature on psychological ownership in human–AI interaction; their bibliometric analysis provides conceptual context rather than a test of familiarity effects. Measured task behaviour offers a complementary perspective. Umair et al. [76] compared paper-based, monitor-based and immersive building-design reviews with 96 civil-engineering postgraduate students. Their measures included task completion time, detected errors, cognitive load and situational awareness. Improved task performance coexisted with greater cognitive demand, illustrating why familiarity or expressed confidence alone should not be treated as evidence of effective use. This student-based task study supplies external behavioural evidence, while the present interviews report practitioners' perceptions.

4.2.4. Organisational and National Culture

Participants also located human–automation collaboration within organisational and national culture. Organisational culture shapes shared assumptions about change, responsibility and acceptable technology use, and prior research links it to trust, reliance and acceptance [74,77]. P7 summarised this multilevel influence: "Also, the culture effect, such as organizational culture and national culture." Although brief, the account indicates that role allocation is not determined at the individual level alone.

Role allocation can be examined in relation to organisational, industry and national contexts [78]. A digitally supportive culture can legitimise experimentation and clarify expectations for responsible use [74]. This issue is especially relevant in construction, where digital transformation remains uneven relative to other sectors. Culture should therefore be treated as an enabling or constraining condition, not as a sufficient explanation for adoption or decision authority.

4.2.5. Role of Automation in Project Decision-Making

Participants expressed different views on the authority that automation should receive. Several favoured a supportive role in which the system supplies evidence while a human retains the final decision. P6 stated: "I prefer to based on my personal judgement. I regard

the automation as tool. They are best fit in statistical analysis, rather than decision-making. In the future, I will not include automation in decision-making process. They only help us do decision-making, not replace us to do decision-making." P1 similarly observed: "We less rely on BIM. We are not rely on the BIM, model, but just help us to make decision making." Other participants accepted stronger machine control under favourable conditions. P7 stated: "Of course. All the time we think about this issue. You need to know the labor is very expensive, machine and programming are cheap and they can directly control the project without emotion." P4 made this acceptance conditional on data quality: "It depends on the input. Is it correct or not. If it is input is accurate, so for sure we trusted the result and the analysis." These accounts identify input validity, consequences and accountability as considerations in participants' preferences for machine authority.

Prior research distinguishes replacement and supportive roles for technology in organisational decisions [42]: replacement is more plausible for structured operational or tactical decisions, whereas support can extend to less structured and more strategic decisions [12]. Construction practitioners nevertheless tend to favour supportive arrangements even as technical capability increases [79]. Algorithm aversion, job insecurity and limited technical knowledge may contribute to this preference [80]. The evidence therefore supports a three-part taxonomy: human-led, decision support and bounded machine action. It also identifies several conditions relevant to role allocation, including task criticality, input validity, accountability, familiarity and organisational context. However, the interviews did not establish formal decision thresholds or a fixed sequential ordering among these conditions. Figure 4 therefore presents a conceptual role-calibration workflow synthesised from the interview themes and prior literature, rather than an empirically validated decision rule. Technical studies illustrate possible bounds on machine action. Feng et al. [81] use a human digital twin and mixed reality for safe motion planning in industrial human–robot interaction, while Lu et al. [82] model reliability in IoT-enabled human–machine systems with dependent components. Zhang et al. [83] address incomplete observation in a human-following robot through intention estimation and constraints on relative pose. These studies concern defined technical systems and operating conditions; they do not transfer unrestricted decision authority to automation or validate the proposed project-governance workflow.

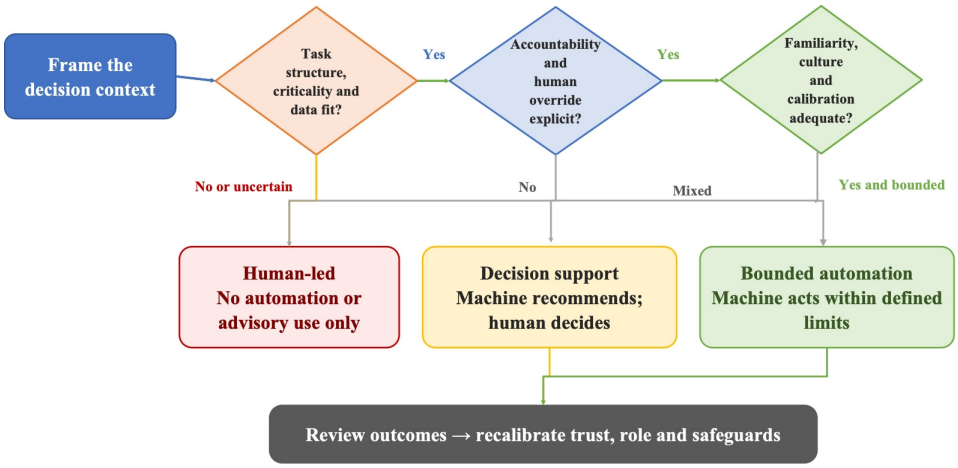


Figure 4. Context-calibrated workflow for assigning automation roles in construction project management.

As a design proposal, the workflow distinguishes human-led decisions, decision support and bounded machine action. It directs attention to task fit, input validity, accountability, override arrangements and user readiness before assigning a system a role. Human

control is retained where uncertainty or consequences warrant it, and the outcome review is proposed as a basis for revising the arrangement.

4.3. Implementation Strategies for Wider Diffusion of Construction Automation

4.3.1. Appropriate Automation

Participants advocated for appropriate automation: technologies should be selected and configured against a defined industry or project need, not adopted because they are fashionable. P13 explained: "We need to check what is enough in terms of automation in construction. Sometimes people just directly use automation, even forget the core objective of using automation. Therefore, we need to balance what is needed in industry? ... What is the optimal level of automation that is required for the industry to ensure work efficiency?" This position corresponds to the concept of effective technology use [84]. A practical implication is to consider the expected value and implementation burden of a technology against the resources and needs of a particular project. The implication is not to slow innovation, but to acquire a credible link between automation and the project problem it is intended to address. Lee et al. [85] provide a concrete construction example: their Web-GIS-based intelligent compaction system connects automated monitoring to compaction-quality assurance, with indicators compared against conventional in situ measurements and demonstrations in two project cases. This shows how an identifiable work need and an explicit assessment procedure can organise implementation; it is not evidence that all management decisions should be automated.

4.3.2. Bottom-Up Implementation

A second recommendation was bottom-up implementation, through which frontline personnel identify, adapt and test automation within their work routines. P13 stated: "So we really need to think about the automation adoption from a bottom-up perspective by applying automation based on the demands, not trends. I believe a bottom-up approach will be more successful in construction automation adoption." Compared with top-down mandates, this approach can engage users, build skills progressively, support change management and reduce resistance [86]. Incremental implementation also limits exposure by confining early use to specific project processes [87]. Its short-term value may be incremental rather than transformative, but it creates feedback for later scaling and aligns technology with actual work practices.

4.3.3. Government and Leading Firms as Change Sponsors

Participants also assigned a change-sponsorship role to government and leading firms. P12 explained: "The Singapore government realized that by aggressively promoting innovative technology, it could leverage its strength, resources, and existing projects. Private companies were unwilling to participate, so the government handled it itself, generating tens of thousands of units annually. The government also directly participated in investment, employing its own developers and bidding processes." The account illustrates how public authorities can use investment, procurement and demonstration projects when private-sector participation is limited. The authors interpret this account as a rationale for considering sponsored pilot projects, shared implementation evidence and access to technical support.

4.3.4. Full-Chain Technology Support

Participants further emphasised the need for full-chain technology support. The focal technology, enabling infrastructure and complementary systems must be developed and implemented together. P12 observed: "For example, when we promote MiC, peripheral

technology also needs to develop simultaneously, such as logistic, BIM and other software and hardware." This lifecycle perspective implies that project organisations must plan not only for the focal tool but also for the data, logistics, software, hardware and work-process changes required for effective integration.

5. Discussion

5.1. Cross-Theme Synthesis

The results converge on six cross-cutting dimensions: readiness and resourcing; motivation and organisational fit; task–technology fit; familiarity, trust and appropriate reliance; accountability and decision authority; and institutional, cultural and ecosystem support. Table 3 distinguishes the interview evidence, interpretive implications and proposed implementation responses for these dimensions. The synthesis positions human–automation collaboration as a sociotechnical governance arrangement rather than a property of an automation system. It identifies operational fit, reliance, accountability and organisational support as considerations for assigning machine authority.

Table 3. The evidence-to-action synthesis for governed human–automation collaboration in project management.

Cross-Cutting Dimension	Interview Evidence and Illustrative Anchors	Interpretive Implication	Proposed Practice/Design Response
Readiness and resourcing	Financial and learning concerns; technical staffing; leadership and implementation support (P1, P2, P6, P10).	Accounts highlighted implementation capacity in addition to access to a technology.	Consider staged investment, training, technical staffing and leadership support.
Motivation and organisational fit	Symbolic adoption and the perceived gap between promotion and work needs; demand for appropriate automation (P2, P13).	Participants distinguished symbolic promotion from purposeful use in project work.	Define the operational problem and expected benefit and then assess fit with the particular organisation and project.
Task–technology fit	Material properties, project stage, decision consequences and input accuracy were cited when discussing suitable machine roles (P4, P10, P11).	Different task contexts were associated with different perceived roles for automation.	Specify the task, valid inputs, operating conditions, decision owner and permitted machine role.
Familiarity, trust and appropriate reliance	Concerns about immature systems and over-reliance; confidence linked to testing and calibration (P6, P8).	Testing and calibration featured as grounds for confidence rather than unqualified trust.	Provide training, test and monitor use, and preserve the capacity for human intervention.
Accountability and decision authority	Ambiguous responsibility after failure; supportive-role preferences and conditional acceptance of greater machine control (P1, P4, P6, P7, P10).	Technical capability and responsibility were treated as distinct concerns alongside divergent role preferences.	Identify an accountable human decision owner, escalation and override arrangements, and whether the system advises, recommends or acts.
Institutional, cultural and ecosystem support	Culture, bottom-up participation, government or leading-firm support and complementary technologies (P7, P12, P13).	Implementation was discussed across individual, organisational and industry contexts.	Consider frontline participation, organisational leadership, demonstration projects and complementary technology support.

Note: Participant identifiers refer to illustrative quotations in Sections 4.1–4.3. Interpretive implications and practice responses are the authors' synthesis, not tested causal relationships or validated prescriptions.

The framework figures synthesise the coded themes rather than represent independently validated models. Figure 3 draws on the adoption themes concerning cost and learning (P6), technical manpower (P2), implementation motivation (P2), digital leadership and implementation support (P1, P2, P10), and appropriate reliance (P6). Figure 4 synthesises the decision-role themes concerning situational and task factors (P10, P11), responsibility and accountability (P6, P10), familiarity and calibration (P8), organisational culture (P7), input quality (P4), and preferences regarding the role of automation (P1, P6, P7). Figure 5 organises the enabling conditions identified across the interviews, including training and familiarity (P2, P6, P8), technical manpower (P2), organisational culture (P7), bottom-up implementation (P13), and government and lifecycle technology support (P12). The relationships between these elements represent an interpretive synthesis of the themes rather than separately coded causal relationships.

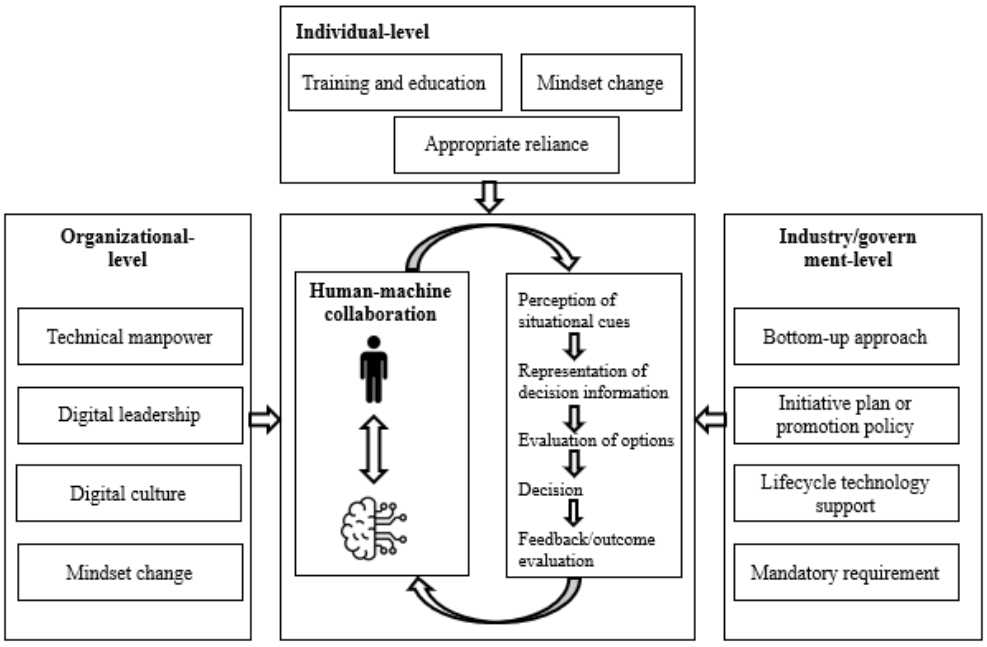


Figure 5. Proposed multilevel enabling conditions for governed human–automation collaboration in construction.

Specifically, Figure 6 integrates these dimensions into a governed architecture for collaborative decision intelligence. It separates the construction project context and accountable human judgement from the digital representation and analytical capability supplied by machines, while connecting contextualisation, explanation, role assignment, decision and outcome learning through a shared governance interface.

In this proposed architecture, practitioners contribute contextual interpretation, consequence assessment and accountable professional judgement, while digital systems contribute representation, analysis, simulation and monitoring. Machine output is treated as evidence for an accountable decision. Figure 5 organises possible supporting actions at individual, organisational and industry/government levels. Training and appropriate reliance concern individual practice; staffing, leadership and digital culture concern organisational arrangements; and promotion policies, shared infrastructure and lifecycle technology support concern for wider institutions. These levels interact: for example, bottom-up participation within organisations can be supported by industry programmes. The figure presents these actions as an interpretive design synthesis.

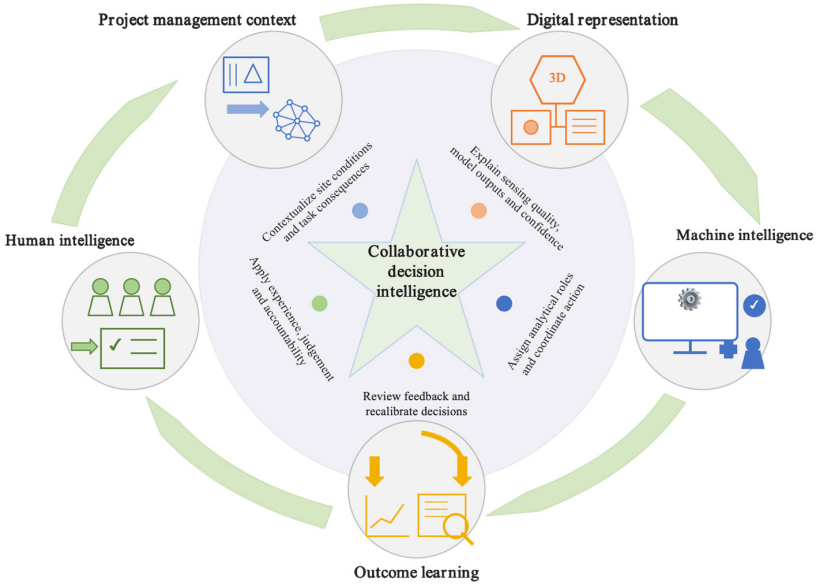


Figure 6. Governed human–automation decision architecture for construction project management.

Together, Figures 5 and 6 distinguish the operating structure of collaborative decision intelligence from the multilevel conditions that sustain it. This distinction is important for project management: assigning a system a role in one decision does not establish readiness for broader deployment.

5.2. Contributions and Project-Management Implications

The first contribution is to connect adoption readiness with the subsequent allocation of decision roles. The interview accounts suggest that introducing a technology does not resolve questions about its authority: participants also discussed task context, familiarity, input quality and responsibility. The framework brings these concerns together with the literature on dynamic resource allocation [88] and task–technology–individual fit [89]. Its contribution is an interview-informed integration of readiness, role calibration and accountability for construction project management. It does not establish a new causal theory or demonstrate that the proposed governance arrangements improve decision performance.

The second contribution concerns construction project management. Because project decisions vary by stage, consequence, structure and stakeholder involvement, machine capability should be translated into a bounded use envelope. For each application, project organisations should identify an accountable decision owner, specify valid inputs and operating conditions, define escalation and override arrangements, and monitor outcomes. These controls connect automation with planning, risk allocation, coordination, monitoring and organisational learning without implying that automation improves cost, schedule or quality in every context.

5.3. Limitations and Future Research

The sample comprises 13 Hong Kong practitioners and supports analytical interpretation rather than population estimates or causal claims. The interviews capture reported experience and preferences, not observed decision performance. Organisation size and project sector are not reported in the participant profile, so comparisons across those groups, or between public and private firms, cannot be made. There is also an approximately five-year gap between data collection in March–December 2021 and this 2026 revision. The accounts predate widespread deployment of large language models and cannot establish how practitioners currently use generative AI or allocate authority to contemporary

AI agents. The later literature contextualises the findings but does not update the interview evidence. Finally, the guide elicited perceptions of machine intelligence, whereas the manuscript interprets those accounts through a broader automation lens; transfer to forms of automation without comparable decision-support functions requires caution. Future research could examine the framework in current project settings and observe whether its proposed accountability, override and feedback arrangements are associated with decision quality and appropriate reliance.

6. Conclusions

This study analysed how 13 Hong Kong construction practitioners described machine intelligence and associated digital decision support in interviews conducted in 2021. Interpreted through a human–automation collaboration lens, their accounts connect adoption concerns with preferences about the role of technology in project decisions. Recurring themes include resources, skills, implementation motivation, leadership, task context, familiarity, input quality and accountability. The proposed governance framework translates these themes into considerations for decision ownership, bounded use, human override and outcome review. These are practice-oriented proposals derived from interview interpretation and the prior literature, not demonstrated effects on adoption or project performance. Their value lies in making the considerations for assigning machine roles explicit. Transfer to other settings requires attention to local tasks, organisations and technologies, and the findings should not be read as evidence of current generative-AI practice. Further empirical work can assess how the proposed arrangements operate in contemporary construction projects.

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Appendix A

Part A Basic information
Q1: Can you introduce your job?
Q2: Have you ever used any form of machine intelligence that support your decision-making?
Q3: Do you find it easy to work with MI?
Q4: How long you have been used the MI in your work? (if yes in Q2)
Part B Characteristics of MI
Q5: Which aspects of the MI did you find pleasant / unpleasant?

Q6: Which characteristics would the MI have to have for you to perceive it as an intelligent system?
Q7: What expectations towards MI do you have if you have to work with it?
Q8: What additional forms of communication would you wish for, if you had to work with the system?
Part C Perception towards MI
(Perception on collaboration)
Q9: How do you perceive collaboration?
Q10: How would you rate the value of collaboration to the success of your work?
Q11: How does a successful collaboration look like?
(Perception on HMI collaboration)
Q12: What is your understanding of MI?
Q13: How do you feel when you think about cooperating with MI?
Q14: Do you have more of a positive or negative feeling when you think about HI-MI collaboration? Why?
Q15: What would a MI be for you? (Tool/Assistant/Peer/Manager)
Q16: What is your preference in decision-making? You rely on the human or MI?
Q17: Do you feel any difference between human-human collaboration and human-machine collaboration? If yes, why?
Q18: What effects will be after introducing MI to workplaces bring on personal and organizational level? How do you feel about it?
Part D: Factors
Q19: What factors would most likely influence your attitude towards MI?

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