

Skilled Software Coder Assessment of the Impact of AI on Coding and Its Implications for Business Development and Sustainability

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ABSTRACT

This pilot study investigates the changing business environment by capturing perspectives of a coding team at a \$100M valued advanced software development firm in Australia. This mixed-methods approach captures quantitative and qualitative data from 13 firm advanced coding developers. The small quantitative data set suited multiple regression analyses of quantitative data under Amos 28.0 and inquisitively assesses qualitative data using NVivo 12.0. The study captures three inbound competencies that support the deployment and actioning of three capabilities. This system of drivers coalesces and delivers a net sustainable business operations outcome. Issues are raised with the use of AI in terms of reliability, over-reliance, assumed learning, and security. Findings show AI is still not fully integrated into the business operations, and so generates opportunities identified by respondent coders for increased automation and efficiency of help desk and other routine operations, improving competitiveness. The gender bias towards males in software development is confirmed by this study. The multiple regression model illustrates AI has a role in improving the firm's ongoing sustainable business operations and efficiency over time. However, many programmers (or coders) are wary of this AI issue, citing security, privacy, and a lack of trust in algorithms used to train advanced digital systems.

Keywords: Artificial intelligence, developer, performance, software, sustainable operations, value.

INTRODUCTION

The business landscape has shifted in the last decade to one of system-driven competitiveness in which tools such as Artificial Intelligence (AI) are often used to undertake tasks once the domain of specialist developers. There is little in the modern business systems architecture development that has not been impacted by the development of AI systems. In particular, the role they have in improving the competitiveness and long-term sustainability of firms, especially those operating in a highly competitive and evolving development market. In particular, the use of AI in software development has enabled the rapid deployment of novel system addons, and this has the potential to impact those who are charged with the development of new products. Currently, AI has a major role in the initial stages of software development, and these tools produce outputs that need to be ameliorated before they can be applied in real-world situations (Raúl et al. 2023).

This study captures an advanced AI coding firm's software development coders' background competencies data as (1) creative technologies (CREATTECHS) where beneficial minimal accurate coding competencies are required (Becker et al. 2023; Vaillant et al. 2024), (2) new capacities (NEWCAPS) that improve coding qualities, work performance and with less coding risks (Derry et al. 2023; Chen et al, 2023), (3) workplace effects (WORKEFF) considered against job prospects, coding versus work functions, AI versus coder replacements, lesser income opportunities (Dobslaw & Bergh, 2023; Vaillant et al, 2023; Hamilton et al. 2023). These three input competencies provide an input suite of considerations into the firm's coders and their subsequent coding capabilities. They indicate that coders must be nimble and actively adapt to ongoing transformations by continuously acquiring new skills and leveraging software and AI skills to boost their competitiveness and achieve ongoing sustainable developments.

In terms of capabilities, this study assesses the advanced AI coding firm against four key software and AI development approaches (1) entrepreneurial risks (BIZRISK) that uses AI to stop unauthorized commercial exploitation of their coding, to help block cyber-attacks and data theft, and to stop cyber criminals controlling their coding (Pham et al, 2022; Ebert & Louridas, 2023; Alenezi & Akour, 2025), (2) delivers business value using AI to improve coding qualities and performances, and to enhance economic rewards through most efficient coding (Alenezi, M., & Akour, M. 2025; Gadani, 2025; Gong et al. 2025), (3) marketplace servicing (SERVICING) by offering AI assisted customer marketplace services (Scott et al. 2022; Murugesan, 2025), (4) operational performance (OPSPERF) creates unique AI enhancements that build aid and deploy top coding skills into aiding competitiveness and sustainability (Hamilton et al. 2024, Schwaeye et al. 2025). These four capabilities constructs, along with their supporting competencies, translate into enhancing ongoing sustainable business operations (SUSTOPS) by delivering competitive AI coding, enhanced AI customer connectivities, high quality AI coding solutions and unique AI connectivities systems as a competitiveness and sustainability outcomes suite (Zhang et al. 2020,

Bruneliere, 2022; Hamilton, et al. 2023). Further publications literature pertinent to regalities around this study are in part contained in a previous ICEB 2022 paper (Ali et al. 2022).

One of the primary concerns with the use of AI in software development is the reliability of the code that is produced, and its ability to be integrated into existing systems (Stavridis and Drugge, 2023). How developers currently perceive the use of AI varies with major concerns surrounding output quality, dependency, and privacy, particularly when the company has its revenue from products that are software-dependent (Giffari et al. 2024; Inman et al. 2025). In particular, this study expands on the links between software and AI developer competencies to their capabilities and through to their delivered sustainable outcomes as discussed in detail previously (Hamilton 2020, 2023; Hamilton et al. 2024). Current understanding of the use of AI by developers can be causally modeled as shown in Figure 1. Considering Figure 1, Semerikov et al. (2020) link competencies to capabilities in software engineering, and loosely consider these as then affecting competitiveness. Zhang et al. (2020) also in part support this causal structure, but only the capabilities related to sustainability relationship components gauged against today's software and AI domains. Thus, this Figure 1 causal model also fits across today's software and AI domains.

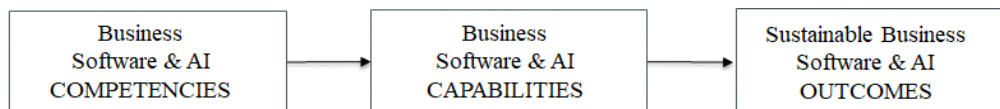


Figure 1. Causal Model Structure for this Study

Aim

This study focuses on a \$100M advanced software development firm in Australia that is pursuing its best solutions towards maintaining its sustainable business operations position in the face of increased customer demand for ever more advanced technical services. Hence, this study pursues, ‘can an Australian Software firm astutely deliver sustainable business operations using AI as a functional tool in coding?’ and so achieve their CEO’s ongoing desire to remain a top digital solutions provider with substantive international reach. This study seeks developers’ (coders’) understanding and perception around how this firm generates or refines its latest digital software using AI towards delivering ongoing digital product solutions that achieve value enhancements, leading to improved operational understanding and risk mitigations.

METHODOLOGY

This mixed-methods pilot study was conducted at an advanced AI coding firm and across its top coding staff in Australia. The data set was developed in conjunction with the firm’s CEO. He sought greater understanding regarding his expert coders, and how they perceived their workplace inputs and actioned capabilities could best deliver a sustainable software and AI coding development operation.

Survey

The opt-in survey was offered to the top development team of 13 individuals with a 100% response rate to demographic questions and qualitative questions, and a 92.3% response rate for the quantitative study (n = 12). While the sample size (n = 13) is not large, this size of sample size is not uncommon in business settings with teams often limited, eg. n = 5 in Giffari et al. (2024). The survey was collected in July 2024. The demographic section of the paper sought data on: the years worked for the firm categorized into cohorts of <2 years, 2-3 years, 4-5 years; the years working as a applications developer/coder categorized into cohorts of <2 years, 2-3 years, 4-5 years, >5 years; the highest qualifications held categorized into cohorts of Diplomas and certificates, Bachelor degree, Master’s degree, PhD; gender had three cohorts of male, female, and other; coder age cohorts of from- 20 to 49 years, 20-24 years, 25-29 years, 30-34 years, 35-39 years, 40-44 years, 45-49 years. The quantitative data set was captured by a Likert scale (1 = strongly disagree to 5 = strongly agree) instrument, generating responses from 24 questions via Google Survey (Table 1). The qualitative study sought responses to eight questions.

Quantitative Analysis

The first statistical analysis for this study applied SPSS version 28.0 (IBM Corp., Armonk, N.Y., USA). The skewness and kurtosis statistics for each question, when tested for normality for each statement set of responses, showed acceptable values of 0 ± 1 , considered near normal, where values of 0 ± 2 are used to determine parametric analysis (Field, 2009). This determined the distribution and variance within the sample to determine data consistency and reliability for further modeling.

The second analysis approach chosen is via multiple regression. This enables a familiar problem solution that focuses on finding a new way to think and understand the situation, whilst simultaneously navigating the AMOS 28.0 stats package. Multiple regression allows analysis between a single endogenous (dependent) variable (sustainable business operations) and a combination of independent exogenous and intermediate endogenous predictor variables. The exogenous variables have no hypothesized origin in the model, but the endogenous variables are presumed to be caused by other or related to other variables in the model (Cunningham, 2008; Hair et al, 2017). Multiple regression allows (1) estimation of the influence of particular predictor variables whilst controlling for the effects of the other variables, (2) optimal linear prediction equations and their

efficacy, (3) testing hypotheses regarding the structural population parameters embedded in the resultant model (Cunningham, 2008; Hair et al, 2017).

Under AMOS 28.0, rather than analysing raw data on a case-by-case basis, this SEM program initially generates a matrix of variances and covariances from the raw data. The data is then associated with an a priori specified model using a maximum likelihood estimation method, provided the data is roughly of normal distribution. A Chi Square statistic, along with the degrees of freedom and the associated p value, is jointly used to determine whether the data set significantly supports the hypothesised model (Cunningham 2008).

The third analysis approach chosen is qualitative and deploys NVivo to capture coder perspectives and opinions. A word cloud and word tree approach is collectively applied across the combined 8 qualitative open-ended questions.

ANALYSIS AND RESULTS

Demographics

The educational achievement of those in the software development sector in this study reveals that respondents did not complete a university bachelor's degree or higher, with the greatest number of respondents holding a Diploma/Certificate (46.2 %), courses designed for under 2 years (Figure 2). This has implications for those seeking entry into the field of programming (or coding) and the educational pathways to achieve impact on the content needed to become functional, and how universities and other educational institutions meet that need outside the standard 3 to 4-year degree programmes. This is reflected historically with the development of associate-level degrees for programming commencing in the 1980s, a trend that has continued (Little 1981). The certificate/diploma pathway entry into industry has remained the standard as skills in the use of AI outputs to generate base code become normalized in the curriculum and workspace (Dowswell, 2024).

This study demonstrated the majority of coders were 26-35 (53.8 %) (Figure 2). Those under 25 represented only 15.4 % of the current workforce (n = 2), while those over 35 represented 30.7% of the workforce (n = 4). The age balance of the firm does not indicate any bias.

The gender results of this study (females n = 1; males n = 12) highlight gender diversity issues that have plagued software development for decades, and this is a consequence of few women in early historical software development and often reinforces the stereotype of a 'boys club' (Wang & Redmiles, 2019; Figure 2). While the use of AI and open source systems has led to increased participation pathways for women in software development (Frluckaj et al. 2022), this study confirms that gender bias exists in the development sector.

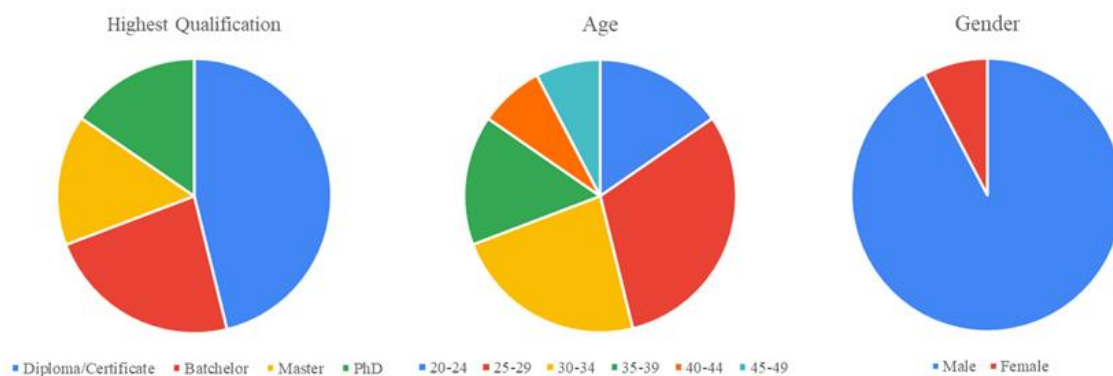


Figure 2. Company survey demographic data showing educational achievement, age and gender of the dedicated software development and coding team.

Results indicate the workforce is relatively new to the firm, with 61.5% of respondents having not worked for the firm for more than 2 years (n = 8), with only one employee working for more than 4 years. Furthermore, results indicate 76.9% of respondents stated this is their first paid employment as a programmer (or coder) (n = 10). This study highlights that the firm's recruitment primarily comprises freshly minted high-skilled programmers, with 84.6 % of respondents having commenced their careers with the firm they currently work for (n = 11; Figure 3).

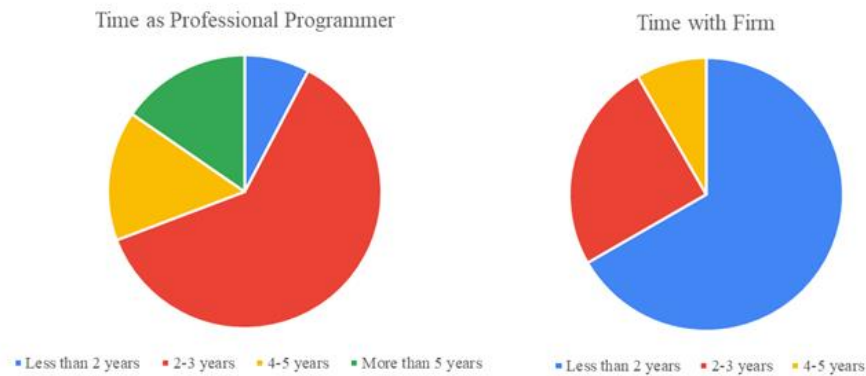


Figure 3. Company survey demographic data showing the length of career in coding and the time of employment with the current firm

Quantitative

The relevant statistical summary of the data set from the survey questionnaire items is allocated to the relevant item measures, each captured under its related specific variable (or construct highlighted) (Table 1). While most answers fell within the disagree-to-agree range, two outliers do exist. The respondents strongly agreed that AI systems will improve the coding and competitiveness of the business, and also improve consumer connectivity, and therefore increase business performance/productivity and sustainability in the long term. The respondents disagreed that AI systems will provide new capabilities and positive workplace effects. This can be qualified with the qualitative results, where a number of respondents noted that AI is trained from existing data and is limited by that data.

Individual survey item measure values are sum-averaged and converted into whole-number construct values. The construct means and standard deviations (columns 12 and 13), together, indicate a slight positive, but near normal bell-curve construct distributions are delivered. The construct means and standard deviations also indicate slightly positive skew, but near normality. Thus, the data set is deemed suitable for AMOS 28.0 multiple regression analysis.

AMOS 28.0 generated a multiple regression path model solution (Figure 4). An attempt to capture and include marketplace serving in the model was unsuccessful because insufficient measurement items were available, and as a single item, this construct inclusion attempt did not fit the model structure. All paths are significant at $p < 0.05$, with the 'work effects-to-business risk' path only significant at $p < 0.05$, and all other paths significant at better than $p > 0.01$. The model is not significant with its Chi Sq/DF ratio between < 3 and > 1 and the p value of 0.122 being above the desired 0.05 value. The Bollen-Stine p value (200 sampling rotations) is also above 0.05, and was used as an attempt to validate the small data pilot set (Cunningham, 2008; Hu & Bentler 1999; Hair et al. 2017). With such a small data set, other fit indices really are not as robust, but the CFI value indicates a fairly good model (> 0.95) (Cunningham, 2008; Hu & Bentler 1999; Hair et al. 2017). Again, TLI and RMSEA were not optimal. In summary, three (3) independent variables, three (3) intermediate variables, and one (1) outcome variable were successfully modeled, but not without very small sample size problems, and there is really not enough evidence to definitely conclude the relationship between input predictor variables and outcome variables is statistically significant at $p < 0.05$, but as all covariance and all regression path weights are all highly or very highly significant, it still suggests a likely multi-stage directional model does exist.

Table 1. Constructs with Item Measures and Data (respondent coders' survey responses).

Construct (and its items)	Respondent Values (scale1-5)	Mean	Std Dev
CRTVTECH (creative technologies)	3 4 2 3 3 3 2 4 3 3 2 4	3.1	0.78
AI used to benefit competencies	3 3 2 3 4 4 2 4 4 4 3 4	3.3	0.75
AI used to minimize coding]	3 4 2 3 3 3 2 5 3 3 1 4	3.0	1.00
AI used for coding accuracy	3 4 2 3 3 3 2 4 3 3 1 4	2.9	0.86
NEWCAPS (new capacities)	3 4 1 3 3 3 2 3 3 3 1 4	2.8	0.91
AI improves coding quality	3 4 1 3 3 3 2 4 3 3 1 4	2.8	0.99
AI improves work performance	3 4 1 3 3 3 2 3 3 3 1 4	2.8	0.92
AI lowers coding risks	3 4 1 3 3 3 3 2 3 3 1 4	2.8	0.92
WORKEFF (workplace effects)	3 3 1 4 4 4 2 3 4 4 3 3	3.1	0.81
AI restricts job prospects	4 2 1 3 3 3 2 2 1 2 1 2	2.2	0.90
AI-based coding affects work functions	3 2 1 3 3 3 2 2 4 2 5 2	2.7	1.03
AI likely replaces coders	1 3 1 3 3 3 1 3 3 4 1 2	2.3	1.03
AI likely reduces income options	2 2 1 3 3 2 1 2 3 4 1 2	2.2	0.90
BIZRISK (entrepreneurial risks)	3 3 1 3 3 4 2 4 3 4 5 3	3.1	0.90
AI helps unauthorized commercial exploitation of coding	3 3 1 3 3 3 1 3 4 4 5 3	3.0	1.08
AI coding is vulnerable to cyber-attack/data theft	3 3 1 3 3 4 3 4 3 5 5 3	3.3	1.03
cyber-criminals can use AI to control our coding	3 3 1 3 3 4 3 4 3 2 5 3	3.1	0.95
VALUES (delivering business value)	3 4 1 3 3 3 3 3 3 5 1 4	3.0	1.07
AI adoption improves coding quality	3 4 1 3 3 3 3 4 3 5 1 4	3.1	1.11
AI adoption improves performance of coding	3 4 1 3 3 3 3 2 3 5 1 4	2.9	1.11
AI adoption improves economic worth of coding	3 3 1 3 3 3 3 2 4 5 1 4	2.9	1.11
SERVICING (marketplace servicing)	3 3 1 3 3 4 4 4 3 3 1 4	3.0	1.00
AI adoption improves customer marketplace services	3 3 1 3 3 4 4 4 3 3 1 4	3.0	1.00
OPSPERF (operational performance)	4 3 1 4 3 4 5 3 3 5 4 3	3.6	0.97
unique AI performance enhancements aid competitiveness & sustainability	3 3 1 3 3 3 5 2 3 5 1 3	2.9	1.19
unique AI pricing aids competitiveness & sustainability	5 4 1 4 3 4 4 4 3 5 5 3	3.8	1.09
unique AI coding skills aid competitiveness & sustainability	5 3 1 5 4 4 5 4 3 5 5 4	4.0	1.15
SUSTOPS (ongoing sustainable operations)	4 4 1 4 4 3 4 3 3 4 3 4	3.3	0.80
unique AI delivered coding aids competitiveness & sustainability	4 4 1 4 4 3 4 4 3 5 5 5	3.8	1.07
unique AI delivered customer connectivities aids competitiveness and sustainability	4 4 1 5 4 4 4 4 3 5 5 5	4.0	1.08
unique AI delivered high quality coding aids competitiveness & sustainability	3 3 1 3 3 3 4 2 3 3 1 3	2.7	0.85
unique AI delivered connectivities systems aid competitiveness & sustainability	3 3 1 3 3 3 5 2 3 3 1 3	2.8	1.01

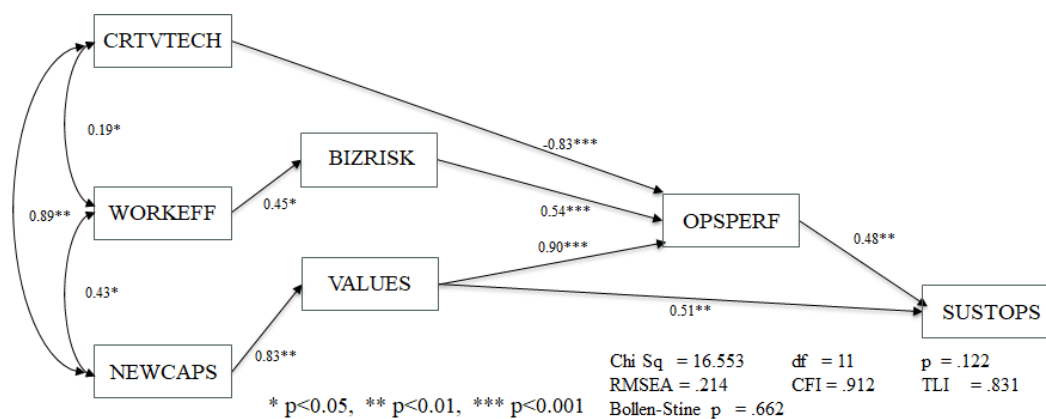


Figure 4. AMOS 28.0 Regression Path Model

Results show some multicollinearity between new capacities and creative technologies and this is as expected. All other correlations reflect suitable and relative relationships as indicated across the model (Table 2). Thus, as sample size is restricted and captures the full number of possible respondents, this model is put forward as a possible way to better understand the firm's senior software development sector.

The responses to the eight qualitative questions were detailed. When asked about the use of AI in daily and domestic activities, most respondents (n = 11) had some varied use of AI, such as the use of AI engines such as *Chat GPT* instead of traditional search engines, as a learning tool seeking assistance with tasks, and responding to emails and creating shopping lists. How respondents used AI in the workplace varies, with 30.8 % not using AI tools, and 38.5 % only using it for email drafting and text creation because “I feel I need a certain level of professionalism”. While 23.1% claim to use AI to produce code for the company, with respondents specifically naming *Github Copilot* and *Chat GPT* for learning and debugging, and coding in JavaScript. When asked how AI could be implemented to improve their jobs, the themes that dominated with improved professionalism, debugging, and automation of “monotonous tasks”.

Results show 2 respondents have no concerns with the current use of AI, while a third noted “when it makes mistakes”. In contrast, the other 10 respondents all had concerns related to accuracy, reliability, over-reliance, assumed learning, and security, with one respondent noting: “It hallucinates, and can misunderstand commands. In the best case, this is inconvenient; in the worst case, this is dangerous”. Furthermore, respondents also noted that AI “is unpredictable and we are putting a great deal of confidence into AI” and “AI requires a lot of information for its learning model, which may not be able to be verified for its security or accuracy due to the sheer amount of coding that requires review”. Results for the respondents’ insights into the greatest scope for AI development in the coding field were dominated by automated tasks, writing text, and the helpdesk was singled out as an area where AI could have its most significant impact. In terms of sustainability for the business, the respondents indicated that efficiency would be of greatest benefit in terms of reduced staffing, particularly in relation to automation of help desk and other routine tasks, as well as improved optimization and allocation of resources in software development, given the ability of AI systems to generate base code.

DISCUSSION

The Figure 4 standardized total effect table (Table 3) indicates that all bar creative technologies positively affect ongoing sustainable business operations, with new capacities providing the strongest independent or input contributions, and values providing the overall strongest intermediate construct contributions. In particular, one unit improvement in new capacities delivers a 0.84 unit improvement in values, a 0.75 unit improvement in operations performance, and a 0.79 unit improvement in ongoing sustainable business operations. Thus, by adding new instruments or techniques, such as a new program or a new version of the latest Chat GPT, to those of the skilled software and AI developer coders, they can soon deliver a real enhancement to the ongoing sustainable business operations and competitiveness of their firm.

Table 3. Model Standardized Total Effects

Standardized Total Effects	WORKEFF	NEWCAPS	VALUES	CRTVTECH	BIZRISK	OPSPERF
VALUES		0.84				
BIZRISK	0.45					
OPSPERF	0.25	0.75	0.90	-0.83	0.54	
SUSTOPS	0.12	0.79	0.95	-0.40	0.26	0.48

The quantitative regression modelling of Figure 4 suggests four pathways (creative technologies to operational performance to sustainable business operations, work efficiencies to operational performance to sustainable business operations, new capacities to values to operational performance to sustainable business operations, and new capacities to values to sustainable business operations exist and each can be independently adjusted to deliver enhanced firm outcomes.

The qualitative NVivo word tree (Figure 6) suggests coders see (1) providing coding, and/or (2) assistance, and/or (3) providing help as key initiating pathway points towards framing the firms’s software and AI solutions. These then support the delivery of advanced software and AI development tasks, applications, and real-time engagement solutions. Progressing further to the right, the word tree’s stagewise enhancement structure is further understood as an approach providing stepwise premium solution component considerations for each of the external contracting firm’s development solutions.

CONCLUSION

A \$100M advanced software development firm in Australia in pursuit of its best solutions towards maintaining its sustainable business operations position in the face of increased global competition aims to find ‘can an Australian Software firm astutely deliver sustainable business operations using AI as a functional tool in coding?’ and so achieve its CEO’s desire to remain a top digital solutions provider with substantive international reach.

This study quantitatively finds the firm’s advanced AI coding developers (coders) can gauge against a suite of inbound competencies, including creative technologies, workforce effort, and new capacities. These collectively can support the firm’s ongoing actions and developing capabilities (business risk, value enhancements, and operational performance), and the six

construct instigation of software and AI changes as a model can be gauged towards delivering a net sustainable business operation.

Qualitatively, this study finds that coders understand the use of AI and AI engines in daily and domestic activities, provide learning and debugging tools, assistance with tasks, improvements to professionalism, automation of monotonous tasks, respond to communications, create new code with relevant sourcing, and improve their jobs. However, concerns regarding accuracy, reliability, over-reliance, assumed learning, security, and command interpretation are noted. Overall, qualitative findings show AI, when used to generate base-code, brings workplace efficiency, improved optimization, and better allocation of resources in software development. When NVivo assessed coders show skilled understanding of their roles as time-efficient AI-assisted code deliverers with added capabilities to assist in creative usage tasks, automation activities, research work, accuracy, security, client learning, data coding, efficient communicative responses, creative improvements, and time-efficient research solutions.

Thus, this mixed methods study concludes AI is still not fully integrated into the firm's business operations, and so generates opportunities identified by respondent coders for increased automation and improved internal efficiencies. The multiple regression model illustrates AI has a role in improving firm's ongoing sustainable business operations and efficiency over time. However, some coders remain wary of AI, citing security, privacy, and a lack of trust in algorithms used to train some aspects of their most advanced digital delivery solutions or systems.

FUTURE STUDIES

This research can be further investigated in future studies by expanding the data set capture beyond that of the senior software developers, and so providing more statistical validity, or by engaging and adding another leading-edge software developer firm or coding firm of similar size, and experience. Assuming the study remained small in size, it could also be investigated under nonparametric or grounded theory approaches.

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