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Exposure to Automation Explains Religious Declines

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Abstract (151/250 words)

The global decline of religiosity represents one of the most significant societal shifts in recent history. After millennia of near-universal religious identification, the world is experiencing a regionally uneven trend towards secularization. We propose a new explanation of this decline, which claims that automation—the development of robots and artificial intelligence (AI)—can partly explain modern religious declines. We build four unique datasets comprised of more than 3 million individuals which show that robotics and AI exposure is linked to 21st century religious declines across nations, metropolitan regions, and individual people. Key results hold controlling for other technological developments (e.g., electricity grid access, telecommunications development) and socioeconomic indicators (e.g., wealth, residential mobility, demographics), and factors implicated in previous theories of religious decline (e.g., individual choice norms). We also experimentally replicate these correlational studies. Our findings partly explain contemporary trends in religious decline and foreshadow where religiosity may wane in the future.

Significance Statement (109/250 words)

The rise of working robots and artificial intelligence (AI) is changing how humans work and live. Many studies have now examined the economic impact of automation on unemployment, income inequality, and trade. However, far less research has considered the broader cultural implications of robotics and AI. Here we show that exposure to robots and AI explains religious declines across national cultures, regions within a nation, members of a community, and employees in an organization. These effects hold controlling for wealth, SES, exposure to science, political conservatism, and other technological advances. Our findings suggest that the rise of automation could accelerate secularization throughout the 21st century in many world regions.

Introduction

Religious decline is accelerating in many world regions. The percent of people identifying as non-religious has risen more than 10% in nations such as Singapore, Iceland, Chile, and South Korea over the last 10 years (1). The percent of religious "nones" in the United States (US) only rose from 3% to 10% between 1948-2005, but then doubled between 2005-2020 (2). Why is religion falling in some regions, and why are these declines accelerating in the 21st century? Just as importantly, why is religious decline so uneven—occurring rapidly in some places while others remain highly religious or become even more religious (1)? Religious decline has no single cause, but there may be broad factors that are facilitating this trend, and identifying these factors could explain which groups and individuals are most likely to lose their faith. We suggest that automation is one of these factors, and that the rise of automation may explain religious declines across multiple levels of analysis.

Automation refers to robotics and artificial intelligence (AI) technology, which has exponentially advanced in the 21st century. Automation has transformed medicine (3), agriculture (4), meteorology (5), and the service industry (6). New AI programs such as ChatGPT and Midjourney show the capacity of AI to generate human language and art. These AI innovations have been especially prominent in nations like Singapore, South Korea, and the US, which have also experienced notable 21st century religious declines (7). This correlation does not prove any meaningful connection between automation and religious decline, but several lines of research also raise significant reasons why people living and working in automated spaces may become less religious. We especially draw from converging scholarship suggesting that automation may reduce the instrumental value of religion.

In addition to drawing existential and moral value from religion, people use supernatural beliefs for instrumental functions. In many folk religions, shamans use divination rituals to predict weather patterns, fetal sex, and to determine the best cures for illnesses (8,9). In world religions like Christianity, people pray more and report more subjective faith in God when they fall ill or experience financial hardship (10–12). Technological advancements give people secular alternatives to fulfill these instrumental goals. When people can use technology to predict the weather, diagnose and treat illness, and manufacture resources, they may rely less on religious beliefs and practices for these specific problems (8).

There is a widespread view among scientists of religion that new technologies may reduce the frequency of some supernatural practices but are insufficient to produce wholesale religious decline. Religion remained stubbornly persistent to the encroachment of science and technology during the industrial revolution (13). Ethnographic fieldwork often reports that people retain supernatural beliefs as ultimate explanations of how technology works (14–16). Cognitive science experiments find that Christians believe that religion works in ways that science cannot understand (17,18). People continue to associate a range of abilities with supernatural agency, even those under the purview of modern science such as curing terminal illnesses (11,19,20). These studies have led scholars of religion to reject Max Weber's rationalist prediction that a rise in science would result in the "disenchantment of the world."

Automation, however, represents a new frontier of technology with novel characteristics. Here we suggest that exposure to new automation technology (robotics and AI) may encourage religious declines, even above and beyond general exposure to science and other forms of technology. This claim is based on recent research on lay perceptions of automation. Such studies show that people ascribe automation technology with abilities that border on supernatural. For example, people perceive Google as having a unique level of agency shared only by Christians' perceptions of God (21), and associate robots and AI with gods more than with humans (22). In many domains, people trust algorithms over trained human experts, a phenomenon called "algorithm appreciation" (23). These perceptions are not always merited, as humans often surpass algorithms in predictive abilities. Nevertheless, many believe that AI allows people to "play god" in a way that previous scientific and technological advances have not, with some commentators suggesting these perceptions will persist as AI becomes increasingly sophisticated (24).

We document evidence of these perceptions in Study S1 (see supplemental materials). This study shows that participating in a day-long seminar on AI led business executives (*n* = 76) to believe that automation allows humans to “break” laws of nature, gives humans “superhuman” abilities, and allows humans to “do things that we have never been able to do before.” We propose that exposure to automation may decrease religiosity because of this perception of human exceptionalism: Historically, people have deferred to supernatural agents and religious professionals to solve instrumental problems beyond the scope of human ability. These problems may seem more solvable for people working and living in highly automated spaces.

These mechanisms underlying automation and religious decline resemble Norris and Inglehart’s existential security model of secularization (25–27), but also contain distinct elements. The existential insecurity model predicts that rising wealth and stability has driven religious decline because people have experienced fewer of the existential concerns that make religion appealing (25). This thesis is supported by research showing that religiosity rises following natural disasters and warfare (28,29), and falls when countries become wealthier and more prosperous (25). Our automation hypothesis resembles this model because new forms of automation are typically designed to meet human needs and make life easier. But we also emphasize people’s perceptions of whether technology can alleviate their needs and help with goal pursuit. People may perceive AI as having capacities that they do not ascribe to traditional sciences and technologies, and that are uniquely likely to displace the instrumental roles of religion. We therefore predict that automation exposure should predict religious declines across nations and people, even controlling for variation in wealth and other forms of technological and scientific exposure.

The primary purpose of this work is to empirically evaluate the link between automation and religious decline, and we do this with four longitudinal studies and one experiment. Our first two studies operationalize automation through international and regional trends in industrial robots. We combine these robotics data with large surveys of religiosity in over 2 million individuals across 68 nations (Study 1) and over 1 million individuals across 110 metropolitan areas in the US (Study 2) to test whether the prevalence of robots can explain which regions of the world and the US have experienced the greatest 21st-century religious declines. At the individual level, we predict that exposure to automated agents should predict religious decline above and beyond exposure to other forms of science and technology. Research on religion and science has found that exposure to science often has little effect on personal religiosity (14,16,30,31). We predict that, unlike science, people’s exposure to automation negatively predicts future religiosity, and could even predict deconversion. In Study 3, we track the religiosity of 69,021 people in New Zealand over 11 years to test whether occupational exposure to AI is associated with losing belief in God. In Study 4, we test whether occupational exposure to AI can explain declining religiosity across employees of an organization in Indonesia as it integrates AI technology.

Our final study is an experiment that tests whether learning about automation technology temporarily reduces religious conviction more than learning about equally impressive scientific advances. We also probe for the properties of automation that may mediate this effect. We acknowledge that a negative effect of automation on religion could be driven by a heterogeneous assortment of mechanisms, which may operate to different degrees in Studies 1-4. In Study 5, we focus on one of these mechanisms, which is people’s belief that AI to operate outside the laws of nature that constrain human science. In our general discussion and supplemental materials, we discuss and empirically test other plausible mechanisms that could explain why religiosity declines in highly automated spaces.

Results

Data and code are available from https://osf.io/stby4/. All statistical tests are two-tailed.

Study 1: Robotics Exposure Explains Religious Declines Across World Nations

Our first study tracked religious declines across world nations. We operationalized automation through each nation’s yearly operational stock of industrial robots, defined as an “automatically controlled, reprogrammable multipurpose manipulator programable in three or more axes” by the International Federation of Robots (IFR). We operationalized religiosity through yearly survey data on the proportion of people across nations ($\sum n$ = 2,014,633) who answered “yes” to the question “Is religion an important part of your daily life?” Variations of this religious importance item are frequently used to measure religiosity across cultures because it can gauge religiosity across a variety of religious traditions and does not make assumptions about religious content (e.g., monotheism). Combining these datasets gave us data on 68 countries from 2006-2019, which we used to test whether robotics exposure could explain 21st century religious decline.

We controlled for several other variables. Our primary control variables involved other forms of technological change: mobile phone subscriptions per capita and the share of population with access to electricity. Measuring telecommunication and energy development allowed us to test the role of robotics above and beyond general technological infrastructure. We also controlled for population size, since operational stock of robots could be larger in more populous countries. We also controlled for GDP per capita and individual choice norms around fertility. We controlled for these latter two variables because the existential theory of secularization suggests that wealth reduces religiosity because it increases certainty and stability (25), whereas other theories focus on value change (32); one view suggests that religious decline occurs when cultures emphasize individual choice norms (e.g., contraception) over pro-fertility norms (27). Our Methods section contains more information about each of these covariates.

Cross-sectional models with intercepts varying randomly across nations found that robotics exposure was robustly and negatively associated with religiosity across the globe (Table 1, Model 1). This negative association replicated controlling for GDP per capita and population size (Table 1, Model 2), and continued to reach significance controlling for telecommunication and energy development (Table 1, Model 3). A longitudinal model with intercepts and slopes randomly varying across nations next estimated whether robotics was linked to declines in religiosity. In this model (Table 1, Model 4), the interaction between robotics and year was significant. This effect replicated controlling for the interaction of telecommunication development with year (Table 1, Model 5) and energy development with year (Table 1, Model 6). Neither energy nor telecommunication development significantly explained declines in religiosity. In the model where we held these covariates constant, nations with a high operational stock (+1 SD) of robots experienced an approximately 3% decline in religiosity per decade ($p = 0.01$), whereas nations with low operational stock (-1 SD) showed approximately a 0.1% increase per decade ($p = 0.95$). This may seem like a small effect, but it was substantially larger than any other geopolitical variable, and these small effects can fuel large divergences in religiosity over time. Figure 1 illustrates these dynamics.

These cross-cultural analyses show that robotics exposure, measured here through the density of industrial robots, can explain variation in religiosity around the world and variation in global religious decline from 2006-2019. Robotics exposure was associated with religious decline above and beyond other forms of technological development, such as telecommunications development and energy development. Each of these results held controlling for GDP per capita and population size.

In our supplemental analyses, we show that key findings replicate when controlling for spatial autocorrelation, and when removing majority-Muslim countries, which had low rates of robot workers and also low rates of religious decline. Analyses also replicate when we interact all variables with year instead of just technological innovations, and when we control for an alternative measure of individualism which is more outdated but includes more nations. One interesting finding that emerges in this supplemental analysis is that individual choice norms around fertility, which have a strong negative cross-sectional relationship with religiosity (see Table 1), do not significantly predict 21st century religious decline. We discuss this curious result more in our general discussion.

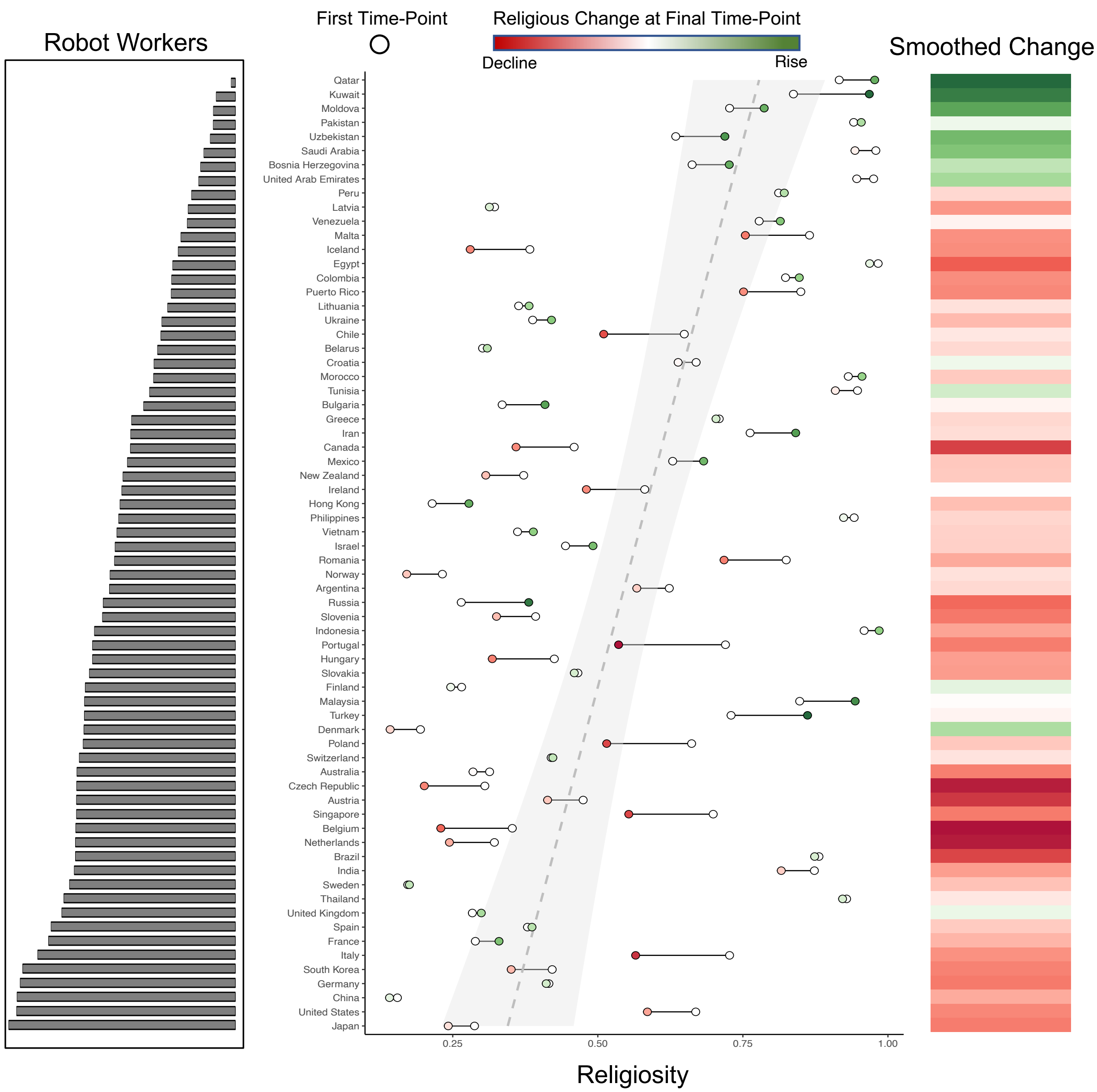

Figure 1. Robotics Exposure and Global Religious Decline. Each nation is ordered in terms of robot prevalence, which is displayed as a log-transformed histogram on the left side of the plot. The central panel shows the mean importance of religiosity for each nation at the first time-point of the dataset (white nodes) and at the final time-point of the dataset (colored nodes). Greener final time-point nodes represent rising religious importance and redder nodes represent declining religious importance. The dashed trend-line represents the correlation between mean importance of religion (across all time-points) and robotics exposure, and the shaded region indicates standard error. The gradient bar on the right side of the plot displays the degree of religious change across the sample of countries more prominently using the same color scheme. This gradient has been smoothed so that each bar indicates the mean religious change score of the horizontally adjacent country and its two y-axis neighbors. The trend-line shows that robotics correlates negatively with religion cross-sectionally, and the color gradient shows that high-robotics countries have experienced greater religious decline than low-robotics countries.

Table 1.
Robotics Exposure and Global Religious Decline

	Religiosity					
	Estimate (SE)					
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.06 (0.12)	0.06 (0.12)	0.04 (0.12)	0.03 (0.12)	0.03 (0.12)	0.02 (0.12)
Robotics Exposure	-0.08*** (0.02)	-0.09*** (0.02)	-0.06** (0.02)	-0.06 (0.03)	-0.06 (0.03)	-0.06 (0.03)
Year				-0.02 (0.02)	-0.03 (0.02)	-0.03 (0.02)
Telecom. Development		0.03** (0.01)	0.04** (0.01)	0.03* (0.01)	0.05* (0.02)	0.04* (0.02)
Energy Development		-0.04* (0.02)	-0.02 (0.02)	-0.01 (0.03)	-0.005 (0.03)	0.005 (0.03)
GDP per Capita			-0.16* (0.07)	-0.07 (0.09)	-0.07 (0.09)	-0.07 (0.09)
Population Size			-0.04 (0.12)	0.04 (0.12)	0.05 (0.13)	0.05 (0.13)
Choice Norms			-0.60*** (0.12)	-0.65*** (0.12)	-0.65*** (0.12)	-0.65*** (0.12)
Robotics Exposure x Year				-0.02* (0.01)	-0.03* (0.01)	-0.03* (0.01)
Telecom. Development x Year					0.01 (0.01)	0.01 (0.01)
Energy Development x Year						0.01 (0.01)
Observations	809	801	594	594	594	594
Log Likelihood	92.30	90.49	70.71	95.24	92.16	88.90
Akaike Inf. Crit.	-176.60	-168.97	-123.43	-164.49	-156.31	-147.81
Bayesian Inf. Crit.	-157.81	-140.86	-83.95	-107.46	-94.90	-82.00

Note. Estimates are presented outside parentheses, and standard errors are presented inside parentheses. All estimates have been standardized via z-scoring. Exact p values are presented in the supplemental materials. * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Study 2: Robotics Exposure Explains Religious Declines Within a Nation

Study 2 next tested for the relationship between robotics exposure and religious decline within a single nation—the United States of America (USA). Testing the relationship within the USA offered a more conservative test of our hypothesis, since regions within the USA are more religiously homogenous than world nations and have more similar levels of technological development. We therefore could test whether robotics exposure explains religious decline controlling for other variables, such as income, employment rate, and residential mobility, which do vary considerably across regions of the USA and have been linked to automation (33,34).

We again measured religiosity through the self-reported importance of religion—measured from 2008-2016 across metropolitan areas—and measured robotics exposure through the operational stock of industrial robots. Specifically, we used estimates released from the Brookings Institute of each metropolitan areas' percent growth in industrial robot operational stock (henceforth called robotics growth) between 2010 and 2015. We combined these metrics into a dataset which also included estimates of median income, unemployment, and residential mobility (reverse coded as number of non-movers) across metropolitan areas. This dataset contained estimates from 110 metropolitan areas and over 1 million individuals (see materials in methods) within the USA, with time-varying religion data from 2008-2016 and time-invariant data on robotics growth, income, unemployment, and residential mobility. See methods for more information about all variables. Figure S2 is a map of the metropolitan areas in our analysis organized by religious decline and robotics growth.

Cross-sectional models with intercepts varying randomly across metropolitan areas and states found that metropolitan areas with high rates of robotics growth showed no significant differences in religiosity compared to metropolitan areas with low rates of robotics growth (Table 2, Model 1), and this association remained null after controlling for unemployment, median income, population size, and number of non-movers (Table 2, Model 2). This cross-sectional association between robotics growth and religiosity is less meaningful across metropolitan areas than across world nations because the distribution of robot workers in the USA has strong regional constraints based on the availability of warehouse space, unionization density, and proximity to travel networks (35). Our critical test was therefore whether robotics growth would explain religious declines. In this test of change over time—a longitudinal model with random intercepts and slopes—we found that robotics growth interacted with time and significantly explained religious declines (Table 2, Model 3). Metropolitan areas with higher levels of robotics growth (+1 SD) experienced an approximately 3% yearly decline in religion each decade (p = 0.006)—mirroring the effect size we observed in Study 1—while metropolitan areas with lower levels of robotics growth (-1 SD) experienced approximately a 0.5% yearly rise in religion (p = 0.67). This effect replicated controlling for the interaction of income and year (Table 2, Model 4), population size and year, and number of non-movers and year (Table 2, Model 5). No other factor explained religious decline in these models.

Table 2.
Robotics Growth and Religious Decline within the United States

	Religiosity				
	Estimate (SE)				
	(1)	(2)	(3)	(4)	(5)
Constant	-0.10 (0.15)	0.002 (0.14)	0.002 (0.14)	0.001 (0.14)	-0.002 (0.14)
Robotics Growth	-0.02 (0.05)	0.03 (0.05)	0.02 (0.05)	0.02 (0.05)	0.02 (0.05)
Year			-0.02 (0.01)	-0.02 (0.01)	-0.02^{*} (0.01)
% Unemployed		0.10 (0.08)	0.11 (0.08)	0.11 (0.08)	0.10 (0.08)
Median Income		-0.39^{***} (0.08)	-0.39^{***} (0.08)	-0.39^{***} (0.08)	-0.39^{***} (0.08)
Population Size		0.24 (0.13)	0.24 (0.13)	0.24 (0.13)	0.24 (0.13)
Non-Movers		-0.13 (0.12)	-0.12 (0.12)	-0.12 (0.12)	-0.12 (0.12)
Robotics Growth x Year			-0.02^{*} (0.01)	-0.02^{*} (0.01)	-0.02^{*} (0.01)
Median Income x Year				0.01 (0.01)	0.003 (0.01)
Population Size x Year					-0.02 (0.03)
Non-Movers x Year					0.04 (0.03)
Observations	883	856	856	856	856
Log Likelihood	-229.76	-207.11	-210.19	-213.57	-218.11
Akaike Inf. Crit.	469.52	432.22	446.38	455.15	468.23
Bayesian Inf. Crit.	493.44	474.99	508.16	521.68	544.26

Note. Estimates are presented outside parentheses, and standard errors are presented inside parentheses. All estimates have been standardized via z-scoring. % Unemployed is only displayed as a main effect because models failed to converge when % unemployed was interacted with year. Exact p values are presented in the supplemental materials. * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

These analyses show that robotics exposure can explain religious declines within a nation as well as across nations. Robotics growth was associated with religious declines across USA metropolitan areas controlling for changes in income, residential mobility, and unemployment. In our supplemental materials, we present additional analyses where the timespan of religious change is restricted to the same time window in which we have available data on robotics growth (2010-2015).

In sum, Studies 1-2 showed that robotics exposure explained religious decline across and within nations. However, research on the ecological fallacy (36) and Simpson's paradox (37) shows that group-level associations sometimes do not replicate, and can even reverse, at the individual level. Studies 1-2 also focused on exposure to automation through robotics, but this exposure can also happen through occupational work with AI algorithms. Studies 3-4 addressed both of these limitations to show that occupational exposure to AI was associated with declines in religiosity across individuals.

Study 3: AI Exposure Explains Religious Declines in a Community Sample

Study 3 was a pre-registered analysis of occupational AI exposure and religiosity within an 11-wave longitudinal study, which was conducted between 2009-2020 in a community sample. Participants in this multi-wave study answered several questions about their personal characteristics and their social attitudes. Nine waves of the study included binary items asking people if they believed in God and if they identified as religious or non-religious (key religion items were omitted from waves 1 and 6). Participants also free-reported their occupation (if any) in all waves, which was manually coded by research assistants into one of 1036 categories (e.g., "social security assessor," "debt collector"). In total, 69,021 individuals participated in at least one wave of the study and 46,680 individuals reported their religion in multiple waves of the study (see methods and supplemental materials for more information about sample and recruiting). Our critical hypothesis was that occupational AI exposure would be associated with lower religiosity across individuals and religious decline within individuals.

We measured occupational AI exposure by incorporating occupation-level meta-data from O*Net, a large occupational database which has classified occupations based on the importance of different occupational qualities (see Methods for more information). We used data on the importance of programming as a proxy for AI exposure. This proxy appeared face valid since many of the jobs with high importance of programming also involve AI exposure (e.g., "Software Engineer," "Web Developer"). We also controlled for importance of biology, chemistry, mathematics, and medicine/dentistry to ensure that generalized scientific exposure or scientific education did not confound AI exposure. We also controlled for SES, age, gender, and political conservatism (38). Our main analyses focused on God belief because it allowed us to test whether AI exposure was associated with religious beliefs rather than just self-reported importance of religiosity (which we had found in Studies 1-2). We found similar results using the religious identification variable, and we summarize those results in the supplemental materials. In general, God belief was stable across the study—God belief at wave 1 correlated at .75 with God belief at wave 11—but a notable proportion of people (17.39%) changed their belief at least once across waves.

Baseline analyses of occupational AI exposure and God belief showed that a random slopes and intercepts model outperformed a random intercepts model, $\chi^2 = 34.42$, $p < 0.001$. In this random slopes and intercepts model, AI exposure and religiosity were negatively and significantly associated, $b = -0.59$, $SE = 0.06$, $OR = 0.55$, $t = -9.33$, $p < 0.001$, 95% *CI*s [-0.72, -0.47]. Since occupational AI exposure was standardized through z-scoring, the odds ratio suggested that people with jobs that were one standard deviation higher than the mean on occupational exposure to AI were 45% less likely to believe in God compared to people in occupations that had a mean level of exposure to AI. Subsequent models found that this association remained statistically significant controlling for SES, age, gender, and political conservatism (Table 3, Model 1), and after controlling for generalized scientific exposure (Table 3, Model 2). In subsequent models, we added lagged terms representing occupational exposure to AI at previous time-points in the survey. In this model, the second-order lag was significantly negatively associated with God belief above and beyond the contemporaneous effect (Table 3, Model 3; see supplemental materials for models including higher-order lags). Occupational exposure to AI may increase someone's likelihood of losing their belief in God, even if they subsequently move into an occupation that no longer involves AI exposure. Figure 2 visualizes these effects.

We also fit models which used a within-person centering procedure to separately estimate the within-person and between-person associations between occupational AI exposure and God belief *(39)*. In order for these models to converge, we needed to restrict our sample to individuals who participated in at least 6 waves of the survey (n = 5,542). Results showed that occupational AI exposure was negatively associated with God belief at both the between-person level, b = -0.08, SE = 0.01, OR = 0.93, t = -6.74, p < 0.001, 95% *CI*s [-0.10, -0.05], and the within-person level, b = -0.02, SE = 0.008, OR = 0.98, t = -2.43, p = 0.02, 95% *CI*s [-0.03, -0.004]. After controlling for the generalized scientific exposure proxies, these between-person, b = -0.07, SE = 0.01, OR = 0.93, t = -6.59, p < 0.001, 95% *CI*s [-0.10, -0.05], and within-person, b = -0.02, SE = 0.008, OR = 0.98, t = -2.18, p = 0.03, 95% *CI*s [-0.03, -0.002], relationships remained negative and statistically significant. In other words, occupational AI exposure explained variation in religious belief across individuals, but also religious decline in the same individual over time.

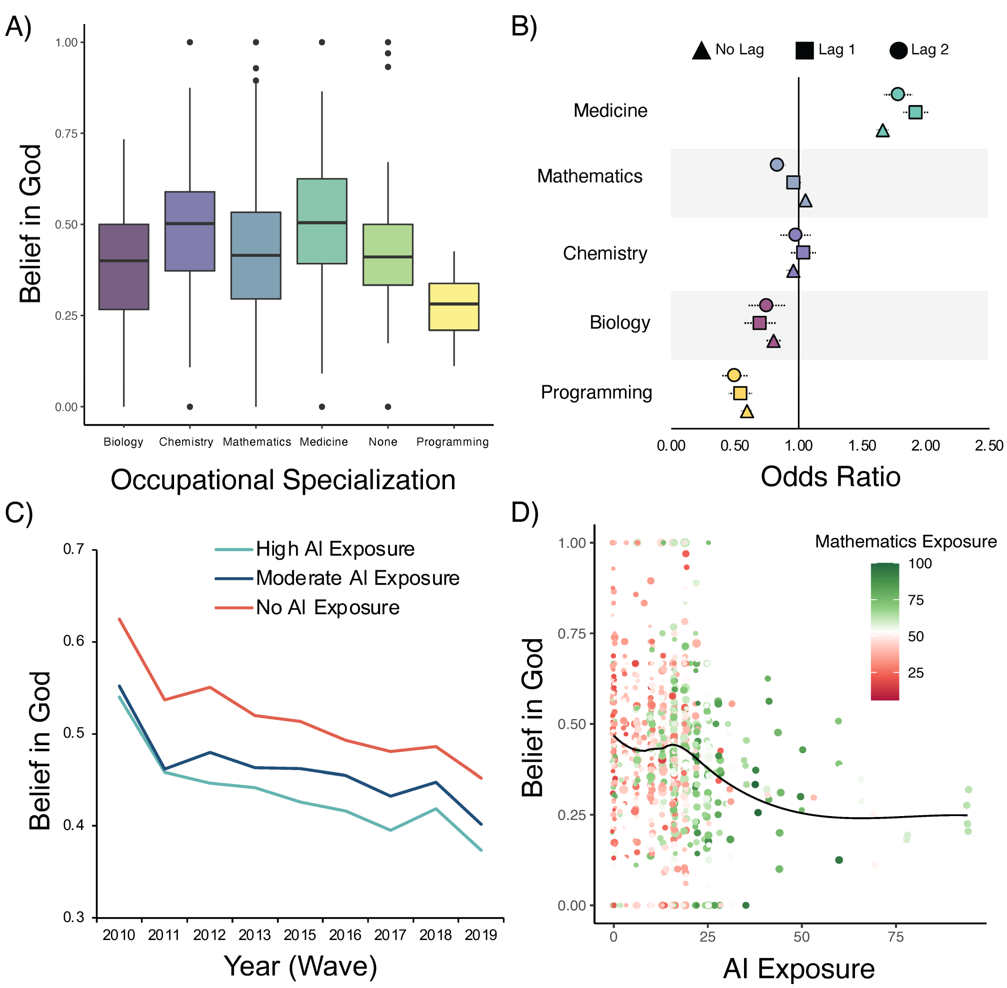

Figure 2. Occupational AI Exposure and Belief in God. Panel A) A boxplot representing the central tendency and distribution of God belief among workers who worked in occupations with high exposure to biology, chemistry, mathematics, medicine/dentistry, programming/AI, or none of the categories (an importance score of less than 25/100 on all science categories). Panel B) The relationship between

exposure to different scientific domains and God belief at no lag, a 1-wave lag, and a 2-wave lag. Dashed error bars represent 95% confidence intervals. Panel C) Average yearly belief in God for people with low AI exposure (first tercile of programming importance), moderate AI exposure (second tercile), and high AI exposure (third tercile). Panel C) A scatterplot of God belief on AI exposure in which nodes represent occupations and node color represents mathematics exposure. The trendline represents a loess curve.

Table 3.
AI Exposure and God Belief in a Community Sample

	Belief in God		
	Estimate (SE)		
	(1)	(2)	(3)
Constant	-2.18*** (0.11)	-2.22*** (0.11)	-1.86*** (0.24)
Timepoint	-0.22*** (0.01)	-0.22*** (0.01)	-0.26*** (0.02)
Income	-0.10*** (0.03)	-0.17*** (0.03)	-0.15* (0.07)
Gender	-2.21*** (0.08)	-2.10*** (0.08)	-2.62*** (0.19)
Age	1.19*** (0.04)	1.18*** (0.04)	1.50*** (0.11)
Conservatism	0.97*** (0.02)	0.97*** (0.02)	0.77*** (0.04)
AI Exposure	-0.53*** (0.04)	-0.52*** (0.04)	-0.11 (0.07)
Biology Exposure		-0.22*** (0.06)	-0.37** (0.13)
Chemistry Exposure		-0.05 (0.05)	-0.03 (0.10)
Mathematics Exposure		0.05 (0.03)	0.02 (0.06)
Medicine/Dentistry Exposure		0.51*** (0.05)	0.76*** (0.10)
AI Exposure (lag 1)			-0.26*** (0.07)
AI Exposure (lag 2)			-0.63*** (0.10)
Observations	106,956	106,392	30,305
Log Likelihood	-48,817.33	-48,509.15	-12,541.42
Akaike Inf. Crit.	97,654.65	97,046.30	25,114.84
Bayesian Inf. Crit.	97,750.46	97,180.35	25,247.95

Note. Estimates are presented outside parentheses, and standard errors are presented inside parentheses. All occupational exposure variables have been standardized via z-scoring for presentation. Exact p values are presented in the supplemental materials. * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Our supplemental materials contain several supporting analyses. These include a replication of our findings using the religious identification as an outcome instead of God belief, robustness checks which replicate our results using different subgroups of participants to rule out the possibility that our findings were confounded with selective attrition, additional descriptive statistics concerning our key variables, additional models which control for general education rather than specific scientific knowledge, and a discussion of alternative modeling procedures. All analyses support our general conclusion that occupational exposure to AI is associated with lower religiosity between individuals and religious declines within individuals.

Study 4: AI Exposure Explains Religious Declines Within an Organization

Study 4 was a pre-registered three-wave (time-lagged) study in which we measured occupational AI exposure in a manufacturing plant as it integrated AI technology. We followed 238 employees within the organization over time, directly measuring their exposure to AI and their religious profiles (intrinsic religiosity, fundamentalism) at Time 1 (T1), their perceived religious importance over the last week and their frequency of religious behaviors over the last week at Time 2 (T2), and supervisor-reports of employee workplace behaviors at Time 3 (T3). Study 4 was the most conservative test of our hypothesis because it featured the smallest and most homogenous sample (participants were primarily Muslim; see methods and supplemental materials) and took place over the narrowest timeframe (three weeks). This study also allowed us to explore the consequences of AI-linked religious decline for workplace behavior.

Because of space limitations, we present the T1 and T2 findings in this paper, which replicate our findings in Study 3. Initial analyses found that T1 AI exposure was negatively associated with T2 religiosity, $r(236) = -0.24$, $p < 0.001$. This association was stronger for the items measuring participants' subjective religious importance over the last week, $r(236) = -0.27$, $p < 0.001$, than for the items measuring frequency of religious behaviors over the last week, $r(236) = -0.17$, $p < 0.001$. This association alone is limited because less religious people may have been faster to adopt AI technology. However, we found that the negative association replicated when we controlled for T1 religious fundamentalism and intrinsic religiosity, $b = -0.18$, $SE = 0.08$, $\beta = -0.19$, $t(229) = -2.17$, $p = 0.03$, 95% *CI*s [-0.35, -0.02], suggesting that AI predicts declines in religiosity as well as cross-sectional variation in religiosity.

We provide more analyses and statistics in our supplemental materials. These analyses also consider downstream associations with participants' T3 workplace behaviors that have been linked to religiosity (40–42) (e.g., unethical behavior, trust, incivility, organizational citizenship behavior, which are face-valid indicators of prosociality). We find that declines in religiosity predict changes in many of these variables.

In sum, Studies 3-4 showed that exposure to AI is linked to declines in religiosity at the individual level. Occupational exposure to AI correlated with lower levels of religiosity across and within individuals, even controlling for covariates. Moreover, AI exposure predicted future declines in religion.

Study 5: Learning About AI Decreases Religious Conviction in an Experimental Paradigm

Our final study was a pre-registered experiment testing whether learning about advances in AI would temporarily decrease religious conviction to a greater extent than learning about other scientific advances. This experiment also explored the properties of AI that might explain why learning about AI reduces religious conviction. We were particularly interested in whether people perceive AI, like God, to operate outside the laws of nature compared to traditional sciences such as chemistry, biology, and medicine. To do this, we asked people whether they associated AI and other scientific advances with discovering and applying "laws of nature," with the implicit view that domains associated with laws of nature like gravity, matter, and motion would be more constrained by these laws. This approach has limitations (e.g., being associated vs. constrained by laws of nature are not interchangeable), but we felt this approach was less demand-laden than nudging participants to think of automation vs. science as God-like, which could interfere with our central dependent variable, religious conviction.

We used a between-subjects design to test our hypotheses. A general sample of 1400 participants with a range of religious beliefs (see Methods)—were randomly assigned to read about three advances in science or AI, which were matched on domain (e.g., language, medicine, or agriculture) and length (one paragraph). For example, participants in the AI condition read about ChatGPT, whereas participants in the science condition read about a new study showing that Broca's area is involved in the production of sign language. Participants rated each automation/scientific advance on its impressiveness, technological sophistication, and the extent that it was associated with laws of nature. They also rated the extent that each advance increased vs. decreased their religious conviction (see Methods for more details).

We fit general linear models with Gaussian estimation testing whether AI advances decreased religious conviction relative to science advances, controlling for their impressiveness and technological sophistication. AI advances were rated as similarly impressive to science advances, $b = 0.04$, $SE = 0.06$, $t = 0.66$, $p = 0.51$, *95% CIs* [-0.08, 0.17], and more technologically sophisticated than scientific advances, $b = 1.26$, $SE = 0.07$, $t = 18.27$, $p < 0.001$, *95% CIs* [1.13, 1.40]. Our results are virtually identical regardless of these controls (see supplemental materials).

As we predicted, participants viewed AI advances as less associated from laws of nature than scientific advances, $b = -1.56$, $SE = 0.08$, $t = -20.34$, $p < 0.001$, *95% CIs* [-1.71, -1.41]. We also found that participants reported less religious conviction in the AI condition vs. the science condition, $b = -0.71$, $SE =$

0.10, *t* = -6.95, *p* < 0.001, *95% CIs* [-0.91, -0.51]. The effect on religious conviction was larger among participants who identified as religious, *b* = -1.05, *SE* = 0.14, *t* = -7.36, *p* < 0.001, *95% CIs* [-1.34, -0.77], than non-religious, *b* = -0.19, *SE* = 0.10, *t* = -1.85, *p* = 0.06, *95% CIs* [-0.39, 0.01], presumably because religious conviction had a greater range of variance for religious participants. Effects broken down by each domain of innovation are summarized in Figure 3. Figure 3 also reports a 5,000-sample bootstrapped mediational model in which find that the association with laws of nature fully mediated the effect of automation on religious conviction.

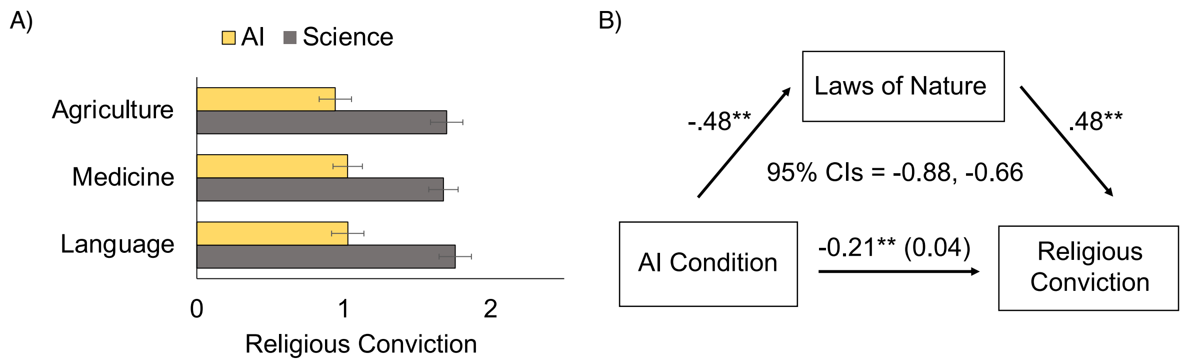

Figure 3. Illustration of Study 5 Results. Panel A) Mean religious conviction for participants in the AI and science conditions of Study 5. D) Estimates from a 5,000-sample bootstrapped mediation model, fit in lavaan for Study 5, in which association with laws of nature fully explains why learning about AI reduces religiosity more than learning about science.

Discussion

The expression “Deus ex Machina,” or “God out of the Machine,” describes an improbable event that resolves a literary plotline. The expression is a metaphor; God does not actually appear out of machines in these stories. But the expression’s inverse could be more literal. Over the last several decades, the world has witnessed a kind of “Machina ex Deus”: Innovations in AI and robotics have spread rapidly around the world and captured public interest, whereas religiosity has declined in many regions at a historically unprecedented pace (1). Here we suggest that these trends are not correlated by coincidence, but that there are meaningful properties of automation which encourage religious decline.

We support our hypothesis with five studies comprising millions of people. Our studies show that religious declines have been fastest in nations (Study 1) and geographical regions (Study 2) with high levels of robots, and that this relationship cannot be explained by key technological or socioeconomic variables. We also found that entering occupations that involve more AI exposure is associated with lower levels of religiosity between individuals and declining belief in God within individuals (Study 3), and that exposure to AI is associated with religious decline in an organization incorporating AI technology (Study 4). In Study 5, we show that learning about advances in AI is associated with greater reductions in religious conviction than learning about scientific advances. Our studies demonstrate that automation is linked to religious decline across multiple religious traditions (e.g., Christian, Muslim, Buddhist), world regions (e.g., North America, South Asia, Oceania), and levels of analysis.

Our supplemental materials provide robustness tests for each of our studies, and they also summarize additional studies which explore nuances and implications of these findings. Study S1, as noted in the introduction, finds that learning about AI in an intensive day-long seminar increased people’s belief that technology has given humans superhuman abilities (i.e., to “play God” and “break laws of nature”). Attending this seminar also decreased the perceived importance of prayer and service attendance at work among highly religious people, but not less religious people. Studies S2-3 explore how religiosity correlates with favorability towards automation. Religious people around the world and across the United States are less favorable to automation than non-religious individuals, even controlling for their favorability towards science (Study S2), and view automation as less compatible with religion than scientific disciplines (Study S3). There are multiple potential explanations behind this negative correlation. For example, favorability towards automation may lead to religious decline, resulting in a negative correlation between the variables. Religious individuals may also report more negative attitudes towards automation because they feel more threatened by automation than non-religious individuals.

Our introduction focuses on the possibility that automation is decreasing the instrumental value of religion. However, we also acknowledge that there may be other mechanisms at play across our studies, and we empirically explore these mechanisms in our other supplemental studies. For example, one alternative mechanism is that the activities and challenges inherent in occupations involving automation are less likely to inspire religiosity compared to the activities and challenges involved in occupations that do not involve automation. Study S4 finds some support for this mechanism, showing that activities associated with AI occupations are viewed as more focused on mechanistic "how" questions rather than existential "why" questions, and by virtue of this association, they are less likely to inspire religious devotion than activities associated with other fields of science and technology. Finally, Study S5 tests whether religious people anticipate becoming less religious when they enter a job in AI vs. in medicine, providing evidence that religious individuals accurately predict the religious declines that we observed in Study 3. Altogether, these studies further support our hypothesis, but also foreshadow future research questions (e.g., to what extent do people make a conscious decision to deconvert in automated spaces?).

There are important limitations of this research program. For example, our theory focuses on religion as a way to satisfy instrumental human needs, but people also turn to religion for moral guidance and purpose. Because people are generally averse to machines making decisions in moral contexts (43), religion might endure as a moral institution in the age of automation. This is ultimately an open question, however, given the emergence of AI in moral decision-making (44) and given that some people have begun losing faith in religion's moral value (particularly in Catholic cultures where church scandals have undermined the moral authority of the church) (32). We encourage future research that integrates these streams of research to identify the distinct causes of religious decline. In our supplemental materials, we write more about how to synthesize these different literatures.

Another limitation of our research is that we conceptualized automation broadly. For example, in Studies 1-2, we measured automation through the size of the robotics industry, whereas in Studies 3-4 we measured automation through individual people's workplace exposure to AI. At the national and regional level, it is difficult to disentangle these measures. Nations with large robotics industries also have higher levels of AI integration than nations with smaller robotics industries (7). However, these different kinds of automation exposure could be studied separately at the individual level, and we encourage future research to test how different kinds of automation exposure may have different effects on religious decline. For example, when automation resembles mechanization (e.g., factory assembly lines), people should be less convinced of automation's potential to impact and improve human life. We encourage future research to test whether these occupations are boundary conditions for our theory.

In early theories of secularization, Marx (45), Weber (46), Durkheim (47), and Freud (48) each wrote that technological advancements inherent in industrialization would contribute to a widespread loss of religion. Contrary to these predictions, industrialization did not spell the end for religion. But automation may bring late vindication for this thesis, at least in industrialized countries. Our findings show that the rise of AI and robotics has been a crucial and overlooked mechanism for explaining religious declines. Our data do not imply that religion is facing worldwide extinction—if anything, religion is polarizing across world regions. But our studies do suggest that current trends in automation may foreshadow religiosity trends in the near and distant future.

Materials and Methods

Our supplemental materials contain additional information about sampling and variable characteristics. All code is publicly available at https://osf.io/stby4/. This project page also contains pre-registrations for Studies 3-5 and our supplemental studies. The page also contains all non-proprietary datasets. The Gallup datasets for Studies 1-2, and the NZAVS dataset, are proprietary and cannot be shared publicly. Readers may obtain these datasets by contacting the authors.

Study 1

Industrial Robots. Our estimates of industrial robot operational stock came from the International Federation of Robots (IFR). The IFR defines industrial robots as “automatically controlled, reprogrammable multipurpose manipulators programmable in three or more axes.” The IFR provides yearly estimates of industrial robots installed across all sectors, but also separately provides the number of robots installed in construction, electricity, manufacturing, mining, and agriculture. We log-transformed the operational stock estimates prior to analyses since they showed a strong positive skew.

Religiosity. Our estimates of religiosity came from the Gallup World Poll, which is the most comprehensive longitudinal and global source of data on religion. The Gallup World Poll surveyed 2,014,633 between 2006 and 2020 with the question “is religion an important part of your daily life?” Although this item does not assess specific religious beliefs, it is a widely used measure of religiosity because it applies to people from a variety of religious traditions, and it has been commonly used in cross-cultural studies. Participants answered the item using “yes” or “no,” and the Gallup World Poll publicly published yearly data on the proportion of people in each society who answered “yes.”

Technological Development. Our estimates of the share of people with mobile phone subscriptions came from the International Telecommunications Union, which publishes yearly data on the number of mobile phone subscriptions per 100,000 people. Estimates of the share of people with access to electricity came from the World Development Indicators, which is published yearly by the World Bank. See supplemental materials for more information. We log-transformed both technological development indicators prior to analyses since they showed a strong positive skew.

Control Variables. We operationalized wealth as GDP per capita based on purchasing power parity (PPP) in 2017 US dollars, which we retrieved for each country-year observation using data from the World Bank. No data were available from Venezuela, and so Venezuela was not included in models controlling for GDP per capita. Estimates of population size came from the United Nations Population Division. We log-transformed both GDP per capita and population size prior to analyses since they showed a strong positive skew. We computed individual choice norms using the same six items as Inglehart (27): whether homosexuality, divorce, and abortion are ever justifiable, whether men have a greater right to a job than women, and whether higher education is more important for boys than girls. We computed two versions of this scale: individual choice norms from countries’ most recent wave of the WVS at the time of our Gallup Data, and the average of countries’ individual choice norms across waves 5 and 6, which overlapped with our Gallup data. The two metrics correlated highly (r = .99), and the results were identical with either measure. We use the most recent scores here. Fewer datapoints were available for our analyses including individual choice norms because we could only analyze nations (n = 49) which had data available from both the WVS and Gallup.

Study 2

Robotics Growth. The Brookings Institute published data—originally gathered by the IFR—on the percent change in industrial robots across American metropolitan areas from 2010-2015, using the same definition of industrial robots as our measure in Study 1. Increases in industrial robots ranged from 1.75% in Shreveport-Bossier City, Louisiana to 33.50% in Charleston, West Virginia. Unlike our nation-level measure of industrial robot operational stock, robotics growth was normally distributed across metropolitan areas.

Religiosity. Our estimates of religiosity came from the Gallup "U.S. Dailies" poll, which asks individuals across metropolitan areas "is religion an important part of your life?" As with the World Poll, U.S. Dailies provides their data in terms of an aggregate percent of the people who respond "Yes" to this question. These data were available from 2008-2016 and contained approximately 175,000 individuals each year.

Control Variables. Our estimates of median income, unemployment, and residential mobility (non-movers) came from the 2010 U.S. Census. Each variable was positively skewed, and so we log-transformed all estimates prior to analyses.

Study 3

Participants. We drew our sample from the 2009-2020 waves of the *New Zealand Attitudes and Values Survey* (NZAVS). The NZAVS is a longitudinal national study of social attitudes, personality, and health outcomes of New Zealanders. The methodology of the study, including the measures and the sampling procedure, have been extensively described in other publications (49,50).

Religiosity. In the main text, we focus on God belief, which was measured by the "yes" or "no" response to the question "Do you believe in a God?" In the supplemental materials, we also analyze data on religious identification, which was measured by the "yes" or "no" response to the question "Do you identify with a religion and/or spiritual group?" The NZAVS has measured other forms of religiosity (e.g., prayer frequency) in select waves, but we focused on items that were measured throughout the course of the study. The NZAVS also measures strength of religious identification within religious individuals, but we did not analyze this item since our focus was on leaving religion.

Occupational AI Exposure. We measured occupational AI exposure through the properties of participants' occupations. Participants in the NZAVS self-reported their occupation, which research assistants then classified into 1036 different unique categories. We trained two research assistants to match these categories into the 874 workplace codes from O*Net based on the responsibilities of the occupation. For example, "Finance Manager" was matched to "Financial Manager" and "Child Care Centre Manager" was matched to "Education and Childcare Administrators, Preschool and Daycare." To ensure that this matching was reliable, the two research assistants completed same 250 occupations and we established that they were translating the occupations at a sufficiently reliable rate (Krippendorf's alpha = .81). Research assistants then divided the remaining occupations and worked separately on matching them. After each NZAVS occupation had been matched to an O*Net code, we downloaded O*Net data on "cross-functional skills" and focused on "Importance of Programming" as a proxy for an occupation in computer science that would involve high occupational exposure to AI.

Study 4

Participants. We invited 250 employees of a food processing manufacturer in Indonesia to participate in our study. Upon receiving the consents, the company administrative team conducted a short briefing with these employees. All surveys were completed in form of paper-and-pencil questionnaires on the last day of the work week and participants in the assembly hall of the company. In total, 238 employees (136 men, 102 women; M_{age} = 33.40, SD_{age} = 8.42; 9 Christian, 191 Muslim, 4 Jain, 6 Ba'hai, 1 Taoist, 5 Non-Religious, 22 "Other") completed all waves, including 36 managers. Participants completed the study across three survey waves, which each occurred a week apart. This time-lagged design is common for capturing dynamics in organizations over time (51,52).

Occupational AI Exposure (T1). We surveyed exposure to AI through a three-item measure in which participants used a 1-5 scale to answer how frequently in the last week they had (a) initiated work-related interaction with AI, (b) interacted with AI at work, and (c) interacted with AI informally at work. Participants were given a definition of AI alongside the items as "systems or software equipped with autonomous learning, problem-solving, and decision-making capabilities, where it can learn from externally acquired data and use learning to achieve specific goals."

Intrinsic Religiosity (T1). Participants completed a short-form of the intrinsic religiosity questionnaire, which was adapted by Schneider, Kriefer, & Bayraktar (53) from Allport & Ross (54). The measure contained eight items, including "I enjoy reading about my religion" and "I try hard to live all my life according to my religious beliefs." Participants answered the items on a 1 (Strongly agree) – 5 (Strongly disagree) scale. We reverse-coded the scale so that higher values meant more intrinsic religiosity.

Religiosity (T2). We measured religiosity using a novel composite scale, with three items tapping perceived religious importance and three items tapping frequency of religious behaviors. Participants rated the importance of (a) God/Allah/gods, (b) prayer, and (c) their religious community from 1 (Not at All Important) – 5 (Very Important). We encouraged participants to focus on their religious "thoughts and activities over the last week" to make the scale more contextually sensitive. Participants rated the frequency of three religious behaviors (attending religious services, reading religious scripture, engaging in religious prayer) over the last week using a 1 (Not at all or less than once) – 5 (Many times) scale. We fit a varimax-rotated maximum likelihood factor analysis to determine that the scale was best captured with a one-factor solution.

Workplace Behaviors (T3). We adapted widely used measures of organizational citizenship behavior, goal progress, counterproductive workplace behavior, incivility, unethical behavior, task proficiency, and trust. We measured each variable using supervisor report (i.e., each employees' behaviors were rated by their immediate supervisor). For the sake of space, we summarize each measure in greater depth and provide sources in the supplemental materials.

Study 5

Participants. Our total sample in Study 5 was 1,371 participants (674 men, 687 women, 9 "Other"; M_{age} = 44.85, SD_{age} = 12.53). This sample combined two studies: A pilot study (*n* = 394), and a pre-registered replication of the pilot (*n* = 977) with distinct samples. The results are identical if we analyze only the main study (see supplemental materials), so we elected to present results with the largest sample size possible. This was a general sample that we did not filter based on religion. In total, 573 participants identified as Atheist (*n* = 166), agnostic (*n* = 233), or as "none" (174) when they reported their religious identity. The most common religious identity was Christian (*n* = 341), followed by Catholic (*n* = 283).

Manipulation. Participants were randomly assigned to the AI (*n* = 687) or science (*n* = 684) condition. Participants in both conditions read about three recent advances. These advances were matched across conditions to focus on language (Chat GPT in the AI condition; a study of Broca's area and sign language in the science condition), medicine (AI-generated X-rays in the AI condition, a study showing the association between Vitamin D and skin cancer in the science condition), and agriculture (IoT in the AI condition, a novel explanation of photosynthesis in the science condition). The advances were described in one paragraph each. We sourced the paragraphs mostly from press releases, and we provide them in the supplemental materials.

Measures. Participants responded to the items (1) "This is an example of discovering laws of nature," (2) "This is an example of applying laws of nature," (3) "This is impressive," (4) "This is technologically sophisticated," (5) "Reading this strengthens my religious conviction," (6) "Reading this makes me feel closer to God." Participants rated these items using a 1 ("Strongly Disagree") – 7 ("Strongly Agree") scale for each domain, and we collapsed across domains in our analyses because results were highly similar for each domain. Items 1-2 indicated association with (vs. dissociation from) laws of nature, items 3-4 were pre-registered control variables, and items 5-6 indicated religious conviction.

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Supplemental Information

1. Supplemental Theoretical Information

Religious decline is a major area of study across the human sciences. We view our research as most relevant to research on religious decline from a cultural evolutionary perspective. Here we expand on this theorizing and situate our research within this broader space.

Cultural Evolutionary Theories of Religion and Religious Decline

There are many models of cultural evolution, but we subscribe to a dual inheritance model in which human behavior and belief systems arises jointly from (a) genetic information, which individuals inherit from their parents via reproduction, and (b) cultural information, which individuals inherit from their society via social learning (1). Therefore, humans might be religious either because they have genetically inherited psychological profiles that make them prone to belief in supernatural agents, or because they have socially learned these beliefs from their parents, peers, and other members of their society.

Findings on the genetic transmission of religion remain mixed (2). Some research has proposed that inherited psychological traits such as intuitive thinking style (3,4), theory of mind (5), and death anxiety (6) predispose individuals to religion. However, large studies have failed to support several of these patterns (7–9), and these bio-psychological mechanisms are poorly suited for explaining cross-cultural variation in religion given their focus on mechanisms shared by all humans. Most comparative studies of religious decline have therefore focused on cultural transmission via social learning.

One class of social learning mechanisms involves the *context* in which people learn about religion, including the person from whom they learn about religion. For example, people are more likely to maintain belief into adulthood if they learn about religion from highly devoted caregivers who regularly signal religious commitment through fasting, attending services, and donating to their religious community (7,10,11). These signals are alternatively described as “credibility enhancing displays” (CREDs) or “honest signals” because they would be extremely costly if people did not authentically hold their beliefs and they therefore provide an honest cue to religious devotion (12). Childhood exposure to CREDs can explain variation in religiosity both inside and outside the United States and can even predict deconversion age among people who grow up in religious households (10). Declining CREDs are therefore important component of religious decline.

A second class of social learning mechanisms focuses on the *content* of religious beliefs. Early content-based hypotheses focused on qualities that made supernatural agents easy to remember and discuss (13–15). For example, the minimally counterintuitive (MCI) hypothesis suggested that people would be more likely to remember gods who selectively violated lay expectations about physics (e.g., by walking on water), biology (e.g., by gaining immortality), or psychology (e.g., by reading minds) than gods who violated none of these lay expectations or who violated all of them (14). Despite widespread interest in the MCI hypothesis, studies supporting the hypothesis have been critiqued because they confound minimally counterintuitive violations with emotionality (e.g., gods possess traits which are emotionally galvanizing), fitness relevance (e.g., gods possess traits that are relevant to survival), and existential relevance (e.g., gods possess traits that threaten or prolong the lives of believers) (16). A more general critique of the MCI hypothesis is that it only explains which agents people *remember;* it does not explain why people become devoted to gods and spirits. This critique is called the “Mickey Mouse” problem because the MCI hypothesis is equally well suited for explaining the evolution of non-worshipped agents like Mickey Mouse and Santa Claus as it is for explaining the evolution of worshipped agents like Jesus or Allah (16). The related “Zeus” problem is that the MCI hypothesis cannot explain why some gods are worshipped in a particular time and place (e.g., the Christian God) whereas others cease to be worshipped (e.g., Zeus) (17).

More recent analyses of content-biased transmission have tried to directly address the Zeus and Mickey Mouse problems. For example, Swan and Halberstadt (18) directly compared characteristics of active gods and other fictional agents (e.g., Mickey Mouse, Zeus), finding that active gods were ascribed more superhuman powers—especially helpful psychological powers—compared to other fictional agents (Mickey Mouse may be unusual, but he does not have special psychological capacities and will not solve your problems). Purzycki and McNamara (19) have argued that gods are usually associated with specific community functions that make them deserving of worship and ritual, such as resource management and social norm regulation. Epley and colleagues (20) made a similar claim by showing that people project their own communal concerns onto gods more than other people (see also Purzycki (21)).

These findings are useful because they show how specific features of gods—namely, the possession of superhuman powers and willingness to use these powers to help resolve human problems—are essential for encouraging demonstrations of religious commitment. In other words, most people perceive religion to have an instrumental function. When people appeal to supernatural agents to help them solve problems, these appeals in turn act as CREDs that inspire the next generation of religious adherents. Content-based dual inheritance models of religious evolution are therefore compatible with context-based models.

Contribution of Our Work

We propose that people's religious worship does not only depend on how they perceive gods and religious role-models; it also depends on how people perceive other means of problem solving. If people believe that automation can address needs that they usually depend on religion to address, they may be less likely to seek out supernatural help through petitionary prayer or ritual participation. In turn, this decline in the frequency of religious displays may lead to broader religious declines. People do not need to explicitly compare automation and religion within this dynamic—which might be highly threatening for a religious individual. Rather, religion may simply be salient to people who have no secular means of solving their problems, and these situations may be rarer for people who have access to automation technology.

Our hypothesis is supported by three well-established premises. The first premise is that people perceive automation and religion as sharing similar features and abilities. For example, people see Google as having uniquely high agency, which is shared only by Christians' perceptions of God (22), and implicitly and explicitly associate robots and AI with gods more than humans (23). Our own studies (Study 5, Study S1) support this idea further by showing that people view automation as operating outside laws of nature, and feel that humans can "break" laws of nature after attending a seminar in AI (Study S1). The evidence in our research and past studies suggests that people think, at least implicitly (23), that automation can fulfill many of the needs that they have previously entrusted to supernatural agents.

The second premise is that people are most likely to engage in religious displays when in need of supernatural aid. For example, prayer and ritual participation increase during natural disasters (24,25) and warfare (26,27), situations in which human science has a limited capacity to help people. Conversely, rises in wealth and stability—which reduce dependence on supernatural aid—have foreshadowed declines in religion in the throughout the 20th century (28,29).

The third and final premise is that declines in religious displays can lead to loss of faith among observers. This hypothesis is well-supported by the CREDs literature (11). Studies of CREDs mostly focus on intergenerational transmission, but declining participation in religious displays may also affect the beliefs of people's peers, or people's own beliefs. Multiple lines of research in social psychology suggest that people use behavioral displays to gauge their own beliefs (30,31). If people pray and attend religious services less frequently, this should have a negative effect on their own beliefs.

As noted throughout the main text, we view automation as only one mechanism of religious decline. Other complementary mechanisms are also plausible. For example, whereas our work focuses on people's perceived need for religion, other research has focused on people's perception of religious institutions. Scandals involving the Catholic Church have served as credibility "undermining" displays (CRUDs) which have turned people away their religious communities and churches (32,33). These value-based perspectives complement our needs-based perspective, which focuses more on the perceived instrumental benefits of religion.

2. Supplemental Information for Study 1

List of Countries by Religiosity and AI Exposure in Study 1

Table S1.
List of Countries in Study 1 by Religiosity and AI Exposure

Country	Years Available	Logged AI Exposure	Religiosity
Argentina	14	7.04	0.62
Australia	13	8.86	0.31
Austria	13	8.88	0.47
Belarus	14	4.35	0.35
Belgium	13	8.93	0.33
Bosnia and Herzegovina	12	1.95	0.73
Brazil	14	8.94	0.88
Bulgaria	12	5.13	0.39
Canada	14	5.87	0.41
Chile	14	4.17	0.64
China	7	12.21	0.15
Columbia	14	3.56	0.85
Croatia	12	4.55	0.64
Czech Republic	12	8.88	0.24
Denmark	14	8.47	0.18
Egypt	11	3.50	0.98
Finland	12	8.39	0.27
France	14	10.44	0.29
Germany	14	12.03	0.40
Greece	13	5.81	0.72
Hong Kong	10	6.45	0.25
Hungary	13	7.99	0.35
Iceland	7	3.20	0.33
India	14	9.01	0.82
Indonesia	14	7.88	0.98
Iran	11	5.86	0.84
Ireland	13	6.35	0.53
Israel	14	6.73	0.48
Italy	14	11.05	0.65
Japan	13	12.67	0.25
Kuwait	4	1.07	0.93
Latvia	13	2.64	0.34
Lithuania	13	3.79	0.40
Malaysia	12	8.43	0.91
Malta	11	3.05	0.82
Mexico	14	6.04	0.64
Moldova	14	1.23	0.73
Morocco	4	4.58	0.95
Netherlands	13	8.94	0.30
New Zealand	13	6.29	0.32
Norway	9	7.01	0.20
Pakistan	14	1.24	0.94
Peru	14	2.45	0.82
Philippines	14	6.53	0.94
Poland	14	8.51	0.64
Portugal	13	7.99	0.62
Puerto Rico	2	3.59	0.80
Qatar	3	0.23	0.95

Republic of Korea	13	11.89	0.41
Romania	13	6.76	0.79
Russian Federation	14	7.39	0.32
Saudi Arabia	4	1.76	0.97
Singapore	13	8.88	0.62
Slovakia	11	8.16	0.46
Slovenia	12	7.43	0.39
Spain	14	10.30	0.39
Sweden	14	9.27	0.18
Switzerland	9	8.73	0.40
Thailand	14	9.59	0.95
Tunisia	11	4.80	0.92
Turkey	13	8.44	0.82
Ukraine	14	4.11	0.44
United Arab Emirates	3	2.05	0.94
United Kingdom	14	9.70	0.29
United States	14	12.23	0.64
Uzbekistan	13	1.41	0.58
Venezuela	14	2.69	0.77
Vietnam	9	6.63	0.34

Note. The AI exposure and religiosity variables are averaged across all available years for each country. The exact years available for each country—and the values for those years—can be found in our Study 1 cleaned dataset on https://osf.io/stby4/.

More Information about Variables in Study 1

Share of Population with Electricity Access. Data on access to electricity are collected among different sources: mostly data from nationally representative household surveys (including national censuses) were used. Survey sources include Demographic and Health Surveys (DHS) and Living Standards Measurement Surveys (LSMS), Multi-Indicator Cluster Surveys (MICS), the World Health Survey (WHS), other nationally developed and implemented surveys, and various government agencies (for example, ministries of energy and utilities). Given the low frequency and the regional distribution of some surveys, several countries have gaps in available data. To develop the historical evolution and starting point of electrification rates, a simple modeling approach was adopted to fill in the missing data points - around 1990, around 2000, and around 2010. Therefore, a country can have a continuum of zero to three data points. There are 42 countries with zero data point and the weighted regional average was used as an estimate for electrification in each of the data periods. 170 countries have between one and three data points and missing data are estimated by using a model with region, country, and time variables. The model keeps the original observation if data is available for any of the time periods. This modeling approach allowed the estimation of electrification rates for 212 countries over these three time periods (Indicated as "Estimate"). Notation "Assumption" refers to the assumption of universal access in countries classified as developed by the United Nations. Data begins from the year in which the first survey data is available for each country.

Share of Population with Mobile Phone Access. Mobile cellular telephone subscriptions are subscriptions to a public mobile telephone service that provide access to the PSTN using cellular technology. The indicator includes (and is split into) the number of postpaid subscriptions, and the number of active prepaid accounts (i.e., that have been used during the last three months). The indicator applies to all mobile cellular subscriptions that offer voice communications. It excludes subscriptions via data cards or USB modems, subscriptions to public mobile data services, private trunked mobile radio, telepoint, radio paging and telemetry services.

Discrepancies between global and national figures may arise when countries use a different definition than the one used by the International Telecommunications Union (ITU). For example, some countries do not include the number of ISDN channels when calculating the number of fixed telephone lines. Discrepancies may also arise in cases where the end of a fiscal year differs from that used by ITU, which is the end of December of every year. A number of countries have fiscal years that end in March or June of every year. Data are usually not adjusted for discrepancies in the definition, reference year or the break in comparability in between years are noted in a data note. Missing values are estimated by ITU.

Results by Type of Robot in Study 1

Study 1 measured log-transformed estimates of industrial robot operational stock from the International Federation of Robots (IFR). The IFR provides yearly estimates of industrial robots installed across all sectors, but also provides the number of robots installed in construction, electricity, manufacturing, mining, and agriculture. In our main text analyses, we focused on overall stock, but here we break down the operational stock based on each sector. These analyses, presented in Tables S2-6 show the same significant findings as our main text across a variety of sectors. We find that the results are similar, and statistically significant, across sectors.

Table S2.
Study 1 Analyses with Robots in Agriculture

	Religiosity					
	Estimate (SE)					
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.06 (0.12)	0.06 (0.12)	0.04 (0.12)	0.03 (0.12)	0.03 (0.12)	0.03 (0.12)
Industrial Robots in Agriculture	-0.09*** (0.02)	-0.10*** (0.02)	-0.07*** (0.02)	0.01 (0.03)	0.01 (0.03)	0.01 (0.03)
Year				-0.03 (0.02)	-0.04* (0.02)	-0.04* (0.02)
Telecom. Development		0.02* (0.01)	0.03** (0.01)	0.03* (0.01)	0.04 (0.02)	0.04 (0.02)
Energy Development		-0.04* (0.02)	-0.03 (0.02)	-0.01 (0.03)	-0.01 (0.03)	-0.001 (0.03)
GDP per Capita			-0.13 (0.07)	-0.12 (0.09)	-0.12 (0.09)	-0.12 (0.09)
Population Size			-0.04 (0.12)	-0.01 (0.12)	-0.003 (0.12)	0.004 (0.13)
Choice Norms			-0.61*** (0.12)	-0.65*** (0.12)	-0.65*** (0.12)	-0.65*** (0.12)
Industrial Robots in Agriculture x Year				-0.03** (0.01)	-0.03** (0.01)	-0.03** (0.01)
Telecom. Development x Year					0.01 (0.01)	0.01 (0.01)
Energy Development x Year						0.01 (0.01)
Observations	809	801	594	594	594	594
Log Likelihood	98.14	95.86	73.25	96.22	93.01	89.70
Akaike Inf. Crit.	-188.27	-179.72	-128.49	-166.43	-158.01	-149.41
Bayesian Inf. Crit.	-169.49	-151.60	-89.01	-109.40	-96.60	-83.60

Note. Estimates are presented outside parentheses, and standard errors are presented inside parentheses. All estimates have been standardized. * $p < .05$; ** $p < .01$; *** $p < .001$.

Table S3.
Study 1 Analyses with Robots in Construction

	Religiosity					
	Estimate (SE)					
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.06 (0.12)	0.06 (0.12)	0.03 (0.12)	0.04 (0.12)	0.03 (0.12)	0.03 (0.12)
Industrial Robots in Construction	-0.07*** (0.02)	-0.09*** (0.02)	-0.06** (0.02)	-0.002 (0.03)	-0.003 (0.03)	-0.01 (0.03)
Year				-0.03 (0.02)	-0.03 (0.02)	-0.03 (0.02)
Telecom. Development		0.02* (0.01)	0.04** (0.01)	0.03 (0.01)	0.04 (0.02)	0.04 (0.02)
Energy Development		-0.05* (0.02)	-0.03 (0.02)	-0.01 (0.03)	-0.01 (0.03)	0.002 (0.03)
GDP per Capita			-0.15* (0.07)	-0.10 (0.09)	-0.11 (0.09)	-0.11 (0.09)
Population Size			-0.04 (0.12)	-0.01 (0.12)	-0.004 (0.12)	0.003 (0.13)
Choice Norms			-0.60*** (0.12)	-0.66*** (0.12)	-0.66*** (0.12)	-0.66*** (0.12)
Industrial Robots in Construction x Year				-0.03* (0.01)	-0.03* (0.01)	-0.03** (0.01)
Telecom. Development x Year					0.01 (0.01)	0.01 (0.01)
Energy Development x Year						0.01 (0.01)
Observations	809	801	594	594	594	594
Log Likelihood	92.82	92.50	71.08	95.53	92.24	88.99
Akaike Inf. Crit.	-177.64	-172.99	-124.16	-165.06	-156.48	-147.98
Bayesian Inf. Crit.	-158.86	-144.88	-84.68	-108.03	-95.06	-82.18

Note. Estimates are presented outside parentheses, and standard errors are presented inside parentheses. All estimates have been standardized here so that effect sizes can be compared. * $p < .05$; ** $p < .01$; *** $p < .001$.

Table S4.
Study 1 Analyses with Robots in Electricity

	Religiosity					
	Estimate (SE)					
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.06 (0.12)	0.06 (0.12)	0.04 (0.12)	0.03 (0.12)	0.03 (0.12)	0.03 (0.12)
Industrial Robots in Electricity	-0.04*** (0.01)	-0.05*** (0.01)	-0.03 (0.01)	0.03 (0.02)	0.03 (0.02)	0.03 (0.02)
Year				-0.04* (0.02)	-0.04* (0.02)	-0.04* (0.02)

Telecom. Development		0.01 (0.01)	0.03** (0.01)	0.03* (0.01)	0.05* (0.02)	0.05* (0.02)
Energy Development		-0.04* (0.02)	-0.02 (0.02)	-0.01 (0.03)	-0.01 (0.03)	0.002 (0.03)
GDP per Capita			-0.19** (0.07)	-0.13 (0.09)	-0.13 (0.09)	-0.13 (0.09)
Population Size			-0.09 (0.12)	-0.03 (0.13)	-0.02 (0.13)	-0.02 (0.13)
Choice Norms			-0.61*** (0.12)	-0.67*** (0.12)	-0.67*** (0.12)	-0.67*** (0.12)
Industrial Robots in Electricity x Year				-0.02* (0.01)	-0.02* (0.01)	-0.02* (0.01)
Telecom. Development x Year					0.01 (0.01)	0.01 (0.01)
Energy Development x Year						0.01 (0.01)
Observations	809	801	594	594	594	594
Log Likelihood	87.50	83.79	67.31	94.09	90.78	87.44
Akaike Inf. Crit.	-167.00	-155.58	-116.61	-162.18	-153.55	-144.88
Bayesian Inf. Crit.	-148.22	-127.46	-77.13	-105.15	-92.13	-79.08

Note. Estimates are presented outside parentheses, and standard errors are presented inside parentheses. All estimates have been standardized here so that effect sizes can be compared. * $p < .05$; ** $p < .01$; *** $p < .001$.

Table S5.
Study 1 Analyses with Robots in Manufacturing

	Religiosity					
	Estimate (SE)					
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.06 (0.12)	0.05 (0.12)	0.03 (0.12)	0.03 (0.12)	0.03 (0.12)	0.03 (0.12)
Industrial Robots in Manufacturing	-0.07*** (0.02)	-0.10*** (0.02)	-0.06** (0.02)	-0.04 (0.03)	-0.04 (0.03)	-0.04 (0.03)
Year				-0.02 (0.02)	-0.03 (0.02)	-0.03 (0.02)
Telecom. Development		0.03** (0.01)	0.04*** (0.01)	0.03 (0.01)	0.05* (0.02)	0.04* (0.02)
Energy Development		-0.04* (0.02)	-0.02 (0.02)	-0.01 (0.03)	-0.003 (0.03)	0.01 (0.03)
GDP per Capita			-0.16* (0.07)	-0.07 (0.09)	-0.08 (0.09)	-0.08 (0.09)
Population Size			-0.03 (0.12)	0.03 (0.13)	0.04 (0.13)	0.05 (0.13)
Choice Norms			-0.60*** (0.12)	-0.65*** (0.12)	-0.65*** (0.12)	-0.65*** (0.12)
Industrial Robots in Manufacturing x Year				-0.03* (0.01)	-0.03* (0.01)	-0.03** (0.01)

	(1)	(2)	(3)	(4)	(5)	(6)
Telecom. Development x Year					0.01 (0.01)	0.01 (0.01)
Energy Development x Year						0.01 (0.01)
Observations	809	801	594	594	594	594
Log Likelihood	92.30	92.50	70.31	95.28	92.45	89.27
Akaike Inf. Crit.	-176.60	-172.99	-122.61	-164.57	-156.89	-148.54
Bayesian Inf. Crit.	-157.81	-144.88	-83.13	-107.54	-95.48	-82.74

Note. Estimates are presented outside parentheses, and standard errors are presented inside parentheses. All estimates have been standardized here so that effect sizes can be compared. * $p < .05$; ** $p < .01$; *** $p < .001$.

Table S6.
Study 1 Analyses with Robots in Mining

	Religiosity					
	Estimate (SE)					
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.06 (0.12)	0.06 (0.12)	0.04 (0.12)	0.04 (0.12)	0.03 (0.12)	0.03 (0.12)
Industrial Robots in Mining	-0.04*** (0.01)	-0.04*** (0.01)	-0.02 (0.01)	0.02 (0.02)	0.02 (0.02)	0.02 (0.02)
Year				-0.04* (0.02)	-0.04* (0.02)	-0.04* (0.02)
Telecom. Development		0.02 (0.01)	0.03** (0.01)	0.03* (0.01)	0.05* (0.02)	0.04 (0.02)
Energy Development		-0.05* (0.02)	-0.03 (0.02)	-0.01 (0.03)	-0.01 (0.03)	-0.001 (0.03)
GDP per Capita			-0.19** (0.07)	-0.11 (0.09)	-0.11 (0.09)	-0.11 (0.09)
Population Size			-0.09 (0.12)	-0.02 (0.12)	-0.01 (0.12)	-0.01 (0.13)
Choice Norms			-0.60*** (0.12)	-0.67*** (0.12)	-0.67*** (0.12)	-0.68*** (0.12)
Industrial Robots in Mining x Year				-0.02* (0.01)	-0.02* (0.01)	-0.02* (0.01)
Telecom. Development x Year					0.01 (0.01)	0.01 (0.01)
Energy Development x Year						0.01 (0.01)
Observations	809	801	594	594	594	594
Log Likelihood	86.99	83.79	67.49	94.34	91.01	87.62
Akaike Inf. Crit.	-165.99	-155.58	-116.98	-162.67	-154.02	-145.24
Bayesian Inf. Crit.	-147.21	-127.47	-77.50	-105.64	-92.60	-79.44

Note. Estimates are presented outside parentheses, and standard errors are presented inside parentheses. All estimates have been standardized here so that effect sizes can be compared. * $p < .05$; ** $p < .01$; *** $p < .001$.

Exact p-Values of Models in Table 1

Table 1 in the main text presents the results of Study 1 with standardized beta values, standard errors, and stars connoting statistical significance. Table S7 presents the same results from Table 1 but with exact *p*-values rather than stars connoting significance.

Table S7.
AI and Global Religious Decline in Study 1 with Exact *p*-values

	Religiosity					
	Estimate (*p* values)					
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.06 (*p* = .65)	0.06 (*p* = .65)	0.04 (*p* = .75)	0.03 (*p* = .79)	0.03 (*p* = .83)	0.02 (*p* = .83)
Robotics Exposure	-0.08*** (*p* < .001)	-0.09*** (*p* < .001)	-0.06** (*p* = .003)	-0.06 (*p* = .08)	-0.06 (*p* = .08)	-0.06 (*p* = .08)
Year				-0.02 (*p* = .19)	-0.03 (*p* = .12)	-0.03 (*p* = .12)
Telecom. Development		0.03** (*p* = .009)	0.04** (*p* = .001)	0.03* (*p* = .04)	0.05* (*p* = .04)	0.04* (*p* = .05)
Energy Development		-0.04* (*p* = .04)	-0.02 (*p* = .24)	-0.01 (*p* = .83)	-0.005 (*p* = .87)	0.005 (*p* = .88)
GDP per Capita			-0.16* (*p* = .02)	-0.07 (*p* = .45)	-0.07 (*p* = .44)	-0.07 (*p* = .44)
Population Size			-0.04 (*p* = .71)	0.04 (*p* = .75)	0.05 (*p* = .71)	0.05 (*p* = .67)
Choice Norms			-0.60*** (*p* < .001)	-0.65*** (*p* < .001)	-0.65*** (*p* < .001)	-0.65*** (*p* < .001)
Robotics Exposure x Year				-0.02* (*p* = .04)	-0.03* (*p* = .03)	-0.03* (*p* = .03)
Telecom. Development x Year					0.01 (*p* = .32)	0.01 (*p* = .48)
Energy Development x Year						0.01 (*p* = .45)
Observations	809	801	594	594	594	594
Log Likelihood	92.30	90.49	70.71	95.24	92.16	88.90
Akaike Inf. Crit.	-176.60	-168.97	-123.43	-164.49	-156.31	-147.81
Bayesian Inf. Crit.	-157.81	-140.86	-83.95	-107.46	-94.90	-82.00

Note. Estimates are presented outside parentheses, and exact *p* values are presented inside parentheses. All estimates have been standardized here so that effect sizes can be compared. * *p* < .05; ** *p* < .01; *** *p* < .001.

Additional Visualizations for Study 1

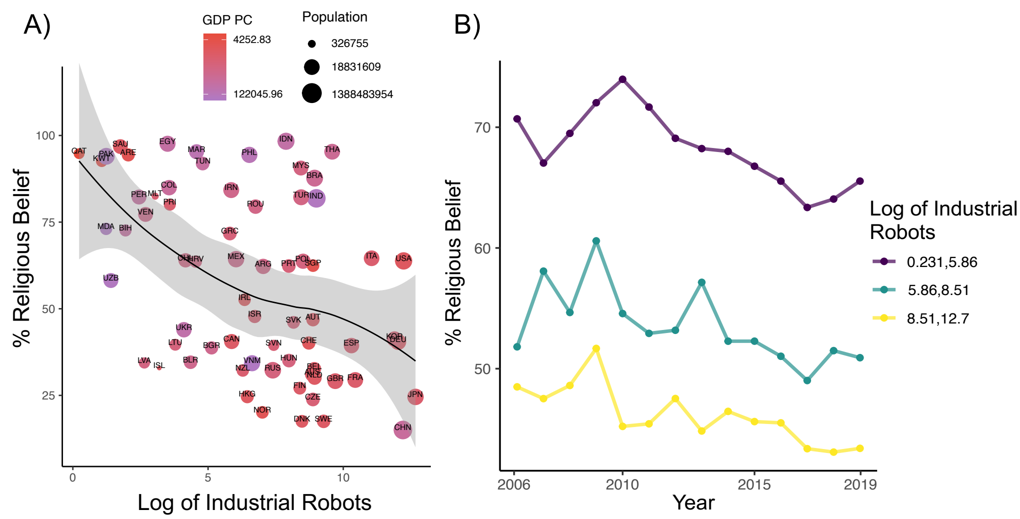

Figure S1. Robotics and Global Religious Decline. Panel A) The cross-sectional association between the operational stock of industrial robots and religious conviction. Nodes represent nations, node size represents population size, and node color represents GDP per capita. Panel B) Yearly religious decline across nations by bottom third, middle third, and top third of industrial robot stock. Line and node color indicate industrial robot stock.

Additional Robustness Checks for Study 1

Table S8 displays two additional Study 1 models which include more robustness checks. Column 1 displays a model in which we interact year with all control variables. Column 2 further includes fixed effects for continents, which controls for spatial autocorrelation, a common source of Type 1 error in cross-cultural surveys. The cross-sectional and longitudinal effects of robotics exposure reach significance in both models. No other factor interacts with time to predict religious decline in these models; choice norms was associated with general levels of religiosity, but not change in religiosity.

Table S8.
Study 1 Robustness Tests

	Religiosity	
	Estimate (SE)	
	(1)	(2)
Constant	0.03 (0.12)	-0.18 (0.25)
Automation	-0.07* (0.04)	-0.07 (0.04)
Year	-0.03 (0.02)	-0.03 (0.02)
GDP per Capita	0.04 (0.02)	0.04 (0.02)
Telecommunications Development	-0.001 (0.03)	-0.01 (0.03)
Energy Development	-0.06 (0.10)	0.02 (0.10)
Population Size	0.04 (0.13)	0.02 (0.12)
Choice Norms	-0.65*** (0.13)	-0.73*** (0.18)
North America		0.51 (0.61)
South America		1.10* (0.44)
Oceania		-0.06 (0.65)

Europe		0.10 (0.37)
Africa		0.81 (0.47)
Automation x Year	-0.04* (0.02)	-0.04* (0.02)
Telecommunications Development x Year	0.01 (0.01)	0.01 (0.01)
Energy Development x Year	0.01 (0.01)	0.01 (0.01)
GDP Per Capita x Year	0.01 (0.02)	0.01 (0.02)
Population Size x Year	0.02 (0.02)	0.02 (0.02)
Choice Norms x Year	0.004 (0.02)	0.003 (0.02)
Observations	594	594
Log Likelihood	80.23	85.68
Akaike Inf. Crit.	-124.46	-125.36
Bayesian Inf. Crit.	-45.50	-24.46

Note. Estimates are presented outside parentheses, and standard errors are presented inside parentheses. * $p < .05$; ** $p < .01$; *** $p < .001$.

Table S9 reproduces Table 1 without majority Muslim nations, which we defined as nations in which at least 50% of the religiously identified population were Muslim. All key main effects and interactions replicated.

Table S9.
Prevalence of Robot Workers and Global Religious Decline Excluding Muslim Countries

	Religiosity					
	Estimate (SE)					
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	-0.03 (0.13)	-0.03 (0.13)	-0.08 (0.15)	-0.11 (0.16)	-0.12 (0.16)	-0.12 (0.16)
Industrial Robots	-0.09*** (0.02)	-0.10*** (0.02)	-0.07** (0.02)	-0.08* (0.04)	-0.08* (0.04)	-0.09* (0.04)
Year				-0.03 (0.02)	-0.03 (0.02)	-0.04 (0.02)
Telecommunications Development		0.03* (0.01)	0.04** (0.02)	0.04* (0.02)	0.05 (0.03)	0.05* (0.03)
Energy Development		-0.04* (0.02)	-0.03 (0.02)	-0.01 (0.03)	-0.01 (0.03)	0.02 (0.03)
GDP per Capita			-0.19* (0.08)	-0.05 (0.11)	-0.06 (0.11)	-0.06 (0.11)
Population Size			0.01 (0.16)	0.18 (0.17)	0.19 (0.17)	0.20 (0.17)
Choice Norms			-0.32 (0.16)	-0.37* (0.16)	-0.35* (0.16)	-0.36* (0.16)
Industrial Robots x Year				-0.03* (0.02)	-0.03* (0.02)	-0.03* (0.02)
Telecommunications Development x Year					0.01 (0.01)	-0.0004 (0.01)
Energy Development x Year						0.03 (0.02)

Observations	692	690	490	490	490	490
Log Likelihood	24.13	19.18	9.51	39.59	36.36	34.84
Akaike Inf. Crit.	-40.25	-26.37	-1.02	-53.18	-44.72	-39.68
Bayesian Inf. Crit.	-22.10	0.85	36.73	1.35	14.01	23.24

Note. Estimates are presented outside parentheses, and standard errors are presented inside parentheses. * $p < .05$; ** $p < .01$; *** $p < .001$.

Table S10 reproduces Table 1 with an alternative measure of individualism: Hofstede's measure of individualism which was available for 64 of the 68 countries in our sample, whereas Inglehart's measure of individual choice norms was available for only 49. Nevertheless, the results are substantively identical with either measure, and we present the choice norms measure in the main text because it is more up to date; Hofstede's measure was based on data collected in the 1980s.

Table S10.
Prevalence of Robot Workers and Global Religious Decline with Hofstede Individualism

	Religiosity					
	Estimate (SE)					
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.06 (0.12)	0.06 (0.12)	0.05 (0.11)	0.05 (0.11)	0.05 (0.11)	0.05 (0.11)
Industrial Robots	-0.08*** (0.02)	-0.09*** (0.02)	-0.08*** (0.02)	-0.08* (0.03)	-0.08* (0.03)	-0.08* (0.03)
Year				-0.04** (0.01)	-0.04** (0.02)	-0.05*** (0.02)
Telecommunications Development		0.03** (0.01)	0.05*** (0.01)	0.05*** (0.01)	0.04* (0.02)	0.05* (0.02)
Energy Development		-0.04* (0.02)	-0.03 (0.02)	-0.01 (0.03)	-0.01 (0.03)	0.04 (0.04)
GDP per Capita			-0.20*** (0.06)	-0.05 (0.08)	-0.05 (0.08)	-0.04 (0.08)
Population Size			-0.05 (0.10)	0.16 (0.10)	0.15 (0.10)	0.17 (0.10)
Hofstede Individualism			-0.47*** (0.11)	-0.56*** (0.11)	-0.56*** (0.11)	-0.57*** (0.11)
Industrial Robots x Year				-0.03* (0.01)	-0.02* (0.01)	-0.02* (0.01)
Telecommunications Development x Year					-0.005 (0.01)	-0.01 (0.01)
Energy Development x Year						0.04* (0.02)
Observations	809	801	750	750	750	750
Log Likelihood	92.30	90.49	99.74	146.36	142.90	142.34
Akaike Inf. Crit.	-176.60	-168.97	-181.47	-266.73	-257.81	-254.68
Bayesian Inf. Crit.	-157.81	-140.86	-139.89	-206.67	-193.12	-185.38

Note. Estimates are presented outside parentheses, and standard errors are presented inside parentheses. * $p < .05$; ** $p < .01$; *** $p < .001$.

3. Supplemental Information for Study 2

List of Metropolitan Areas by Religiosity and AI Exposure

Table S11.
List of Metropolitan Areas in Study 2 by Religiosity and AI Exposure

Metropolitan Area	Years Available	Robotics Growth	Religiosity
Albany-Schenectady-Troy, NY	9	0.30	0.52
Albuquerque, NM	9	0.13	0.63
Anchorage, AK	8	0.19	0.53
Atlanta-Sandy Springs-Roswell, GA	9	0.20	0.74
Augusta-Richmond County, GA-SC	9	0.17	0.79
Austin-Round Rock, TX	9	0.19	0.61
Bakersfield, CA	9	0.21	0.69
Baltimore-Columbia-Towson, MD	9	0.14	0.63
Baton Rouge, LA	9	0.18	0.80
Beaumont-Port Arthur, TX	5	0.20	0.82
Birmingham-Hoover, AL	9	0.26	0.84
Boise City, ID	9	0.20	0.60
Boston-Cambridge-Newton, MA-NH	9	0.18	0.48
Buffalo-Cheektowaga-Niagara Falls, NY	9	0.18	0.60
Burlington-South Burlington, VT	5	0.16	0.41
Cedar Rapids, IA	5	0.17	0.59
Charleston-North Charleston, SC	9	0.17	0.71
Charleston, WV	5	0.34	0.72
Charlotte-Concord-Gastonia, NC-SC	9	0.20	0.75
Chattanooga, TN-GA	9	0.24	0.79
Cincinnati, OH-KY-IN	9	0.21	0.66
Cleveland-Elyria, OH	9	0.17	0.63
Colorado Springs, CO	9	0.16	0.61
Columbia, SC	9	0.21	0.77
Columbus, OH	9	0.15	0.62
Dallas-Fort Worth-Arlington, TX	9	0.18	0.73
Davenport-Moline-Rock Island, IA-IL	5	0.22	0.62
Dayton, OH	9	0.20	0.68
Denver-Aurora-Lakewood, CO	9	0.19	0.55
Des Moines-West Des Moines, IA	9	0.20	0.64
Detroit-Warren-Dearborn, MI	9	0.21	0.64
Duluth, MN-WI	5	0.22	0.60
El Paso, TX	8	0.13	0.73
Erie, PA	5	0.18	0.63
Eugene, OR	9	0.12	0.48
Evansville, IN-KY	5	0.19	0.73
Flint, MI	5	0.14	0.66
Fort Smith, AR-OK	5	0.12	0.77
Fort Wayne, IN	8	0.19	0.71
Fresno, CA	9	0.17	0.68
Grand Rapids-Wyoming, MI	9	0.23	0.68
Green Bay, WI	5	0.21	0.63
Greenville-Anderson-Mauldin, SC	9	0.22	0.80
Harrisburg-Carlisle, PA	9	0.20	0.66
Hartford-West Hartford-East Hartford, CT	9	0.16	0.54

Houston-The Woodlands-Sugar Land, TX	9	0.19	0.73
Huntsville, AL	7	0.13	0.78
Indianapolis-Carmel-Anderson, IN	9	0.16	0.69
Jacksonville, FL	9	0.20	0.69
Kansas City, MO-KS	9	0.20	0.67
Knoxville, TN	9	0.17	0.77
Lansing-East Lansing, MI	6	0.15	0.56
Las Vegas-Henderson-Paradise, NV	9	0.23	0.57
Lexington-Fayette, KY	6	0.15	0.70
Lincoln, NE	5	0.17	0.62
Los Angeles-Long Beach-Anaheim, CA	9	0.16	0.59
Madison, WI	9	0.20	0.48
Medford, OR	5	0.18	0.55
Memphis, TN-MS-AR	9	0.20	0.80
Miami-Fort Lauderdale-West Palm Beach, FL	18	0.18	0.62
Milwaukee-Waukesha-West Allis, WI	9	0.19	0.64
Minneapolis-St. Paul-Bloomington, MN-WI	9	0.19	0.59
Mobile, AL	5	0.29	0.82
Montgomery, AL	5	0.25	0.85
Naples-Immokalee-Marco Island, FL	5	0.27	0.64
New Orleans-Metairie, LA	9	0.21	0.72
New York-Newark-Jersey City, NY-NJ-PA	9	0.17	0.59
Oklahoma City, OK	9	0.20	0.73
Omaha-Council Bluffs, NE-IA	9	0.19	0.65
Orlando-Kissimmee-Sanford, FL	9	0.18	0.66
Peoria, IL	5	0.27	0.67
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	9	0.14	0.60
Phoenix-Mesa-Scottsdale, AZ	9	0.19	0.60
Pittsburgh, PA	9	0.20	0.66
Portland-South Portland, ME	9	0.15	0.45
Portland-Vancouver-Hillsboro, OR-WA	9	0.21	0.50
Providence-Warwick, RI-MA	9	0.19	0.53
Raleigh, NC	9	0.26	0.67
Reno, NV	5	0.20	0.50
Richmond, VA	9	0.20	0.71
Roanoke, VA	5	0.20	0.72
Rochester, NY	9	0.16	0.55
Rockford, IL	5	0.25	0.62
Sacramento--Roseville--Arden-Arcade, CA	9	0.18	0.54
Salt Lake City, UT	9	0.19	0.60
San Antonio-New Braunfels, TX	9	0.18	0.71
San Diego-Carlsbad, CA	9	0.20	0.56
San Francisco-Oakland-Hayward, CA	9	0.26	0.45
Scranton--Wilkes-Barre--Hazleton, PA	9	0.15	0.65
Seattle-Tacoma-Bellevue, WA	9	0.21	0.48
Shreveport-Bossier City, LA	6	0.02	0.83
South Bend-Mishawaka, IN-MI	5	0.09	0.66
Spokane-Spokane Valley, WA	9	0.20	0.59
Springfield, MA	9	0.13	0.51
Springfield, MO	7	0.22	0.72
St. Louis, MO-IL	9	0.21	0.66
Syracuse, NY	9	0.08	0.55
Tallahassee, FL	5	0.11	0.69

Tampa-St. Petersburg-Clearwater, FL	9	0.20	0.63
Toledo, OH	9	0.28	0.63
Topeka, KS	5	0.18	0.65
Tucson, AZ	9	0.18	0.59
Tulsa, OK	9	0.19	0.74
Urban Honolulu, HI	9	0.21	0.56
Utica-Rome, NY	5	0.13	0.58
Virginia Beach-Norfolk-Newport News, VA-NC	9	0.19	0.69
Washington-Arlington-Alexandria, DC-VA-MD-WV	9	0.16	0.62
Wichita, KS	9	0.23	0.71
Wilmington, NC	5	0.13	0.71
Youngstown-Warren-Boardman, OH-PA	9	0.16	0.69

Exact p-Values of Models in Table 2

Table S12.
Robotics Growth and Religious Decline in the United States in Study 2 with Exact *p*-Values

	Religiosity				
	Estimate (95% CIs)				
	(1)	(2)	(3)	(4)	(5)
Constant	-0.10 (*p* < .001)	0.002 (*p* < .001)	0.002 (*p* < .001)	0.001 (*p* < .001)	-0.002 (*p* < .001)
Robotics Growth	-0.02 (*p* = .73)	0.03 (*p* = .53)	0.02 (*p* = .61)	0.02 (*p* = .61)	0.02 (*p* = .60)
Year			-0.02 (*p* = .07)	-0.02 (*p* = .46)	-0.02* (*p* = .48)
% Unemployed		0.10 (*p* = .21)	0.11 (*p* = .20)	0.11 (*p* = .20)	0.10 (*p* = .20)
Median Income		-0.39*** (*p* < .001)	-0.39*** (*p* < .001)	-0.39*** (*p* < .001)	-0.39*** (*p* < .001)
Population Size		0.24 (*p* = .06)	0.24 (*p* = .06)	0.24 (*p* = .06)	0.24 (*p* = .06)
Non-Movers		-0.13 (*p* = .27)	-0.12 (*p* = .31)	-0.12 (*p* = .31)	-0.12 (*p* = .31)
Robotics Growth x Year			-0.02* (*p* = .03)	-0.02* (*p* = .02)	-0.02* (*p* = .03)
Median Income x Year				0.01 (*p* = .35)	0.003 (*p* = .75)
Population Size x Year					-0.02 (*p* = .37)
Non-Movers x Year					0.04 (*p* = .13)
Observations	883	856	856	856	856
Log Likelihood	-229.76	-207.11	-210.19	-213.57	-218.11
Akaike Inf. Crit.	469.52	432.22	446.38	455.15	468.23
Bayesian Inf. Crit.	493.44	474.99	508.16	521.68	544.26

Note. Estimates are presented outside parentheses, and standard errors are presented inside parentheses. All estimates have been standardized for presentation, so that effect sizes can be compared. % Unemployed is only displayed as a main effect because models failed to converge when % unemployed was interacted with year. * $p < .05$; ** $p < .01$; *** $p < .001$.

Visualizing Robotics Growth and Religious Decline Across Metropolitan Areas

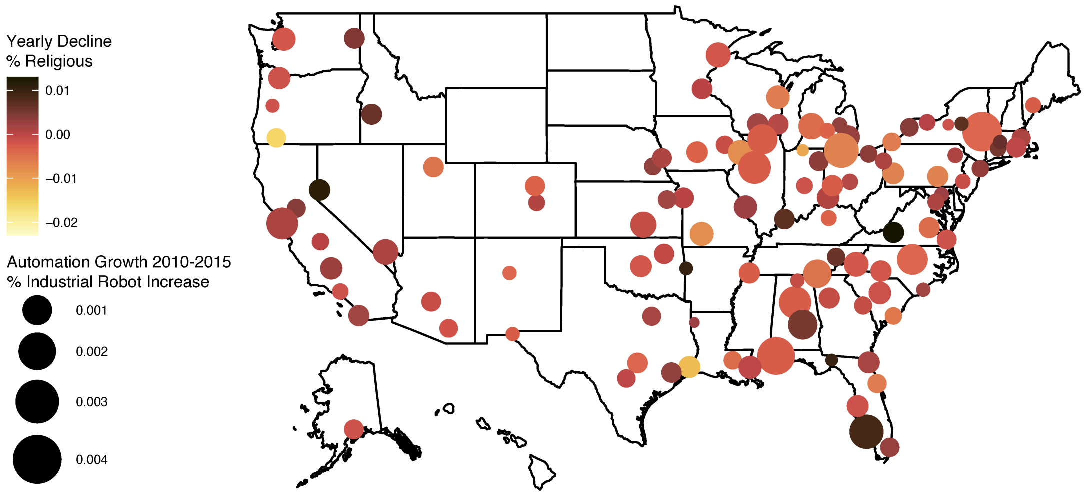

Figure S2. Robotics Growth and Religious Decline across USA Metropolitan Areas. Node color indicates yearly decline in the percent of religious people. Node size indicates robotics growth.

AI Interest and Religiosity Interest in the United States Over Time

Study 2 tested how robotics growth related to religiosity across various American regions. In this study, as in Study 1, robotics growth was associated with religious decline. However, neither Study 1 nor Study 2 featured intensive longitudinal data, which meant that we could not develop pseudocausal models to test whether time-specific increases in robotics growth preceded time-lagged declines in religiosity. We therefore conducted an exploratory analysis in which we used Google Trends to test for the relationship between interest in AI and interest in religion over ten years (2011-2020).

Google Trends is quickly growing as a research tool for quantifying regional and intertemporal variation in preferences and values. One specific advantage of Google Trends is that it is available at the monthly level, whereas many historical surveys (e.g., Gallup World Poll) and corpora (e.g., Google Books) are typically analyzed at the level of the year. Google Trends has also recently been applied to track changes in religious beliefs. Bentzen (34) recently used variation in searches for “prayer” to claim that religious beliefs increased during the COVID-19 pandemic. “Prayer” was a relatively useful keyword in this study because searches for “prayer” are more likely to come from genuine religious belief rather than academic interest in religion (e.g., Atheists may frequently search for “God”) (34).

We built on Bentzen’s (34) study by tracking variation in prayer interest, and also tracking variation in three keywords which connoted interest in artificial intelligence: “AI,” “coding,” and “computer coding.” To reduce researcher degrees of freedom, we pre-registered the study characteristics (e.g., time window and set of terms) before downloading data and running analyses. Our pre-registration is available at https://osf.io/stby4/. A Cronbach’s alpha analysis confirmed that our AI search-terms showed high internal consistency (α = .88), indicating that months with high search volume for “AI” would also have high search volume for “computer coding” and vice versa. We therefore collapsed our AI search-terms so that we had two time-series representing (a) religion interest, and (b) AI interest. Figure S3 displays these time series over our 10-year sample window.

We conducted two time series analyses to determine whether there was a negative lagged relationship between AI interest and religiosity interest. The first analysis was a pre-whitened cross-correlation which visualized the correlation between these two variables at a variety of different lags (e.g., how do changes in AI interest correlate with changes in religiosity interest 5 months later?). "Pre-whitening" a cross-correlation refers to a process where a time series model is fitted to the *x*-variable, extracted, and then used to residualized the *y*-variable, which is a procedure that is meant to remove possible spurious lagged effects arising from autocorrelation or other interdependence in the time series. The second analysis was a vectoral autoregression which models both autoregressive effects (how do changes in variable *x* at time *t* predict changes in variable *x* at time *t*+1), and cross-lagged effects (how do changes in variable *x* at time *t* predict changes in variable *y* at time *t*+1). For both models, we determined the maximum lag (12 units of time) based on a data-driven function which determines the best maximum lag based on AIC fit. For our VAR model, we differenced the time series before analyzing their bidirectional relationship, so as to remove any possible monotonic trend which could yield a spurious positive correlation between interest in religiosity and interest in AI.

Figure S3 presents the results of the cross-correlation, and Table S13 presents the results of the VAR model. Both models showed bi-directional lagged effects between interest in religiosity and interest in prayer. Religiosity interest could predict future declines in AI interest at an optimal lag of 7 months, and AI interest could predict future declines in religiosity interest at an optimal lag of 10 months. The coefficients of these negative effects are displayed on the y-axis of Figure S3, and in Table S13. Overall, this analysis supports our Study 2 conclusion that rises in AI exposure predict declines in religiosity using pseudocausal methods of time series analysis. This analysis also adds an interesting wrinkle to that finding; religiosity also appears to foreshadow declines in AI interest over time, consistent with a negative reciprocal relationship. However, this is a highly exploratory finding, and should be taken with more caution than the results we present in the main text.

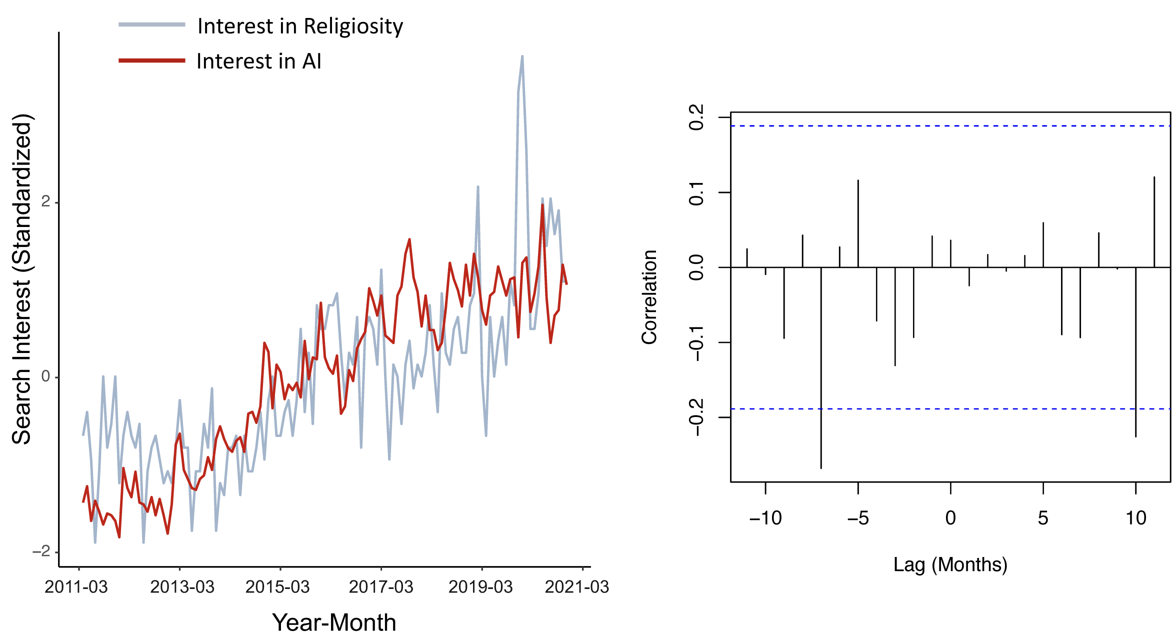

Figure S3. Intertemporal dynamics characterizing interest in AI and interest in religiosity. Left: The raw time-series characterizing interest in prayer (blue) and interest in AI (red). Data are plotted at the monthly level. Right: The results of a pre-whitened cross-correlation between interest in prayer and interest in AI. Each bar represents a correlation at a different lag (bars exceeding the dashed lines are statistically significant), and the lag values *k* are determined on the x-axis. Bars to the left represent religiosity interest predicting AI interest *k*-months in the future; Bars to the left represent AI interest predicting religiosity interest *k*-months in the future.

Table S13.
Lagged Relationship Between Interest in AI and Interest in Religiosity from a VAR Model

Lag	Religiosity Interest Predicting AI Interest	AI Interest Predicting Religiosity Interest
1	.05 (.06)	.01 (.21)
2	-.07 (.06)	-.25 (.23)
3	-.10 (.06)	-.10 (.24)
4	-.08 (.07)	-.37 (.25)
5	.02 (.07)	-.18 (.25)
6	.02 (.07)	-.02 (.25)
7	-.15* (.07)	-.21 (.26)
8	-.09 (.07)	-.06 (.25)
9	-.11 (.07)	-.37 (.25)
10	-.12 (.07)	-.84** (.25)
11	-.05 (.48)	-.08 (.25)
12	-.05 (.38)	-.36 (.24)

Note. Estimates are presented outside parentheses, and standard errors are presented inside parentheses. * $p < .05$; ** $p < .01$; *** $p < .001$.

4. Supplemental Information for Study 3

Descriptive Statistics for Study 3 Variables

Table S14 displays the mean of religious identification and God belief at each wave of Study 3. Table S15 shows the mean of each occupational science exposure variable at each wave of the survey.

Table S14.
Mean of Religiosity Variables at Each Survey Wave

Wave	God Belief	Religious Identification
1	Not Measured	.44
2	.61	.45
3	.52	.40
4	.52	.42
5	.49	.39
6	Not Measured	.40
7	.48	.42
8	.47	.38
9	.45	.36
10	.47	.36
11	.41	.34

Table S15.
Mean of Science Occupational Exposure Variables at Each Survey Wave

Wave	Biology	Chemistry	Mathematics	Medicine	Programming
1	16.94	20.04	51.12	21.07	12.57
2	18.05	20.41	51.25	22.41	12.94
3	17.81	19.20	51.32	21.74	14.05
4	16.39	18.55	50.38	20.62	13.10
5	17.25	18.86	50.54	21.14	13.35
6	17.59	18.99	50.97	21.41	13.89
7	18.02	19.11	50.93	21.89	14.02
8	18.00	19.17	51.14	21.73	14.05
9	18.66	19.33	51.43	22.35	14.55
10	18.19	19.27	51.43	21.60	14.25

11	18.71	19.30	51.46	22.10	14.69

Incorporating Third-Order Lagged Terms in Study 3

In the main text, Table 3 (Model 3) presents a lagged analysis of God belief and occupational AI exposure. We include the first-order and second-order lags, but do not include any higher-order lags because it reduced our sample to only a fraction (n = 8,262) of the total population. Nevertheless, if we included third-order lags, the third-order lagged effect reached statistical significance, b = -.24, SE = .09, OR = .79, t = -2.70, p = .007, 95% CIs [.67, .94], but with a smaller effect size than the first- and second-order lagged terms (bs = -.24 vs. -.28 and -.71, respectively).

Exact p-Values in Table 3

Table S16.
AI Exposure and God Belief in a Community Sample with Exact p-Values

	Belief in God		
	Estimate (SE)		
	(1)	(2)	(3)
Constant	-2.18*** (p < .001)	-2.22*** (p < .001)	-1.86*** (p < .001)
Timepoint	-0.22*** (p < .001)	-0.22*** (p < .001)	-0.26*** (p < .001)
Income	-0.10*** (p < .001)	-0.17*** (p < .001)	-0.15* (p = .02)
Gender	-2.21*** (p < .001)	-2.10*** (p < .001)	-2.62*** (p < .001)
Age	1.19*** (p < .001)	1.18*** (p < .001)	1.50*** (p < .001)
Conservatism	0.97*** (p < .001)	0.97*** (p < .001)	0.77*** (p < .001)
AI Exposure	-0.53*** (p < .001)	-0.52*** (p < .001)	-0.11 (p = .16)
Biology Exposure		-0.22*** (p < .001)	-0.37** (p = .005)
Chemistry Exposure		-0.05 (p = .34)	-0.03 (p = .74)
Mathematics Exposure		0.05 (p = .08)	0.02 (p = .71)
Medicine/Dentistry Exposure		0.51*** (p < .001)	0.76*** (p < .001)
AI Exposure (lag 1)			-0.26*** (p < .001)
AI Exposure (lag 2)			-0.63*** (p < .001)
Observations	106,956	106,392	30,305
Log Likelihood	-48,817.33	-48,509.15	-12,541.42
Akaike Inf. Crit.	97,654.65	97,046.30	25,114.84
Bayesian Inf. Crit.	97,750.46	97,180.35	25,247.95

Replicating Study 3 Results with Religious Identification Instead of God Belief

Table S17.
AI Exposure and Religious Identification in a Community Sample

	Religious Identification		
	Estimate (95% CIs)		
	(1)	(2)	(3)
Constant	-8.87*** (-9.09, -8.64)	-8.86*** (-9.09, -8.64)	-8.30*** (-8.74, -7.87)
Timepoint	-0.10*** (-0.11, -0.08)	-0.10*** (-0.11, -0.08)	-0.15*** (-0.19, -0.12)
Income	0.07* (0.004, 0.13)	0.04 (-0.03, 0.11)	0.08 (-0.06, 0.21)
Gender	-0.42*** (-0.57, -0.27)	-0.38*** (-0.53, -0.23)	-0.48** (-0.79, -0.17)
Age	0.36*** (0.28, 0.45)	0.37*** (0.28, 0.45)	0.38*** (0.20, 0.56)
Conservatism	0.36*** (0.32, 0.40)	0.36*** (0.32, 0.40)	0.33*** (0.26, 0.40)
AI Exposure	-0.63*** (-0.78, -0.48)	-0.60*** (-0.74, -0.45)	0.04 (-0.13, 0.21)
Biology Exposure		-0.09 (-0.23, 0.05)	0.07 (-0.18, 0.33)
Chemistry Exposure		-0.004 (-0.11, 0.11)	-0.06 (-0.27, 0.14)
Mathematics Exposure		0.002 (-0.06, 0.07)	0.03 (-0.09, 0.16)
Medicine/Dentistry Exposure		0.18*** (0.08, 0.28)	0.02 (-0.16, 0.20)
AI Exposure (lag 1)			-0.05 (-0.21, 0.11)
AI Exposure (lag 2)			-0.47** (-0.77, -0.17)
Observations	119,858	119,219	33,992
Log Likelihood	-48,699.85	-48,479.85	-12,899.54
Akaike Inf. Crit.	97,419.71	96,987.70	25,831.08
Bayesian Inf. Crit.	97,516.65	97,123.34	25,966.03

Note. Estimates are presented outside parentheses, and standard errors are presented inside parentheses. All occupational exposure variables have been standardized via z-scoring for presentation. * *p* < .05; ** *p* < .01; *** *p* < .001.

Additional Robustness Tests for Study 3

We conducted several additional analyses to ensure the robustness of Study 3's findings. These included replicating our central models controlling for general education rather than exposure to specific scientific fields and replicating the relationship between AI exposure and God belief in participants who took part in different subsets of NZAVS waves to control for attrition. We describe each of these approaches below.

Controlling for General Education. Our central models control for occupational exposure to biology, chemistry, mathematics, and medicine/dentistry to ensure that knowledge about science did not confound the relationship between AI exposure and God belief. In supplemental models, we replicated this key relationship controlling for education level as a more general proxy for scientific knowledge. Each participant provided their level of education according to the "New Zealand Qualifications Framework" (NZQF), which provides ten levels ranging from certificates to doctoral degrees communicating different levels of educational qualification. For example, a level 1 certificate communicates "Basic general and/or foundational knowledge" and is earned during secondary education, level 7 indicates "Specialized technical or theoretical knowledge with depth in a field of work or study" and connotes a bachelor's degree, and level 10 indicates "Knowledge at the most advanced frontier of a field of study or professional practice" and connotes a doctoral degree. Simultaneously controlling for education and scientific exposure introduced multicollinearity into our models, so instead we present Table S18 below which controls for general education—scored from 1-10 based on the NZQF codes—rather than exposure to specific scientific fields.

Table S18.
Belief in God Models with General Education Control

	Belief in God	
	Estimate (SE)	
	(1)	(2)
Constant	-1.90*** (0.15)	-1.30*** (0.37)
Timepoint	-0.20*** (0.01)	-0.23*** (0.02)
Income	-0.06* (0.03)	-0.05 (0.07)
Gender	-2.24*** (0.08)	-2.76*** (0.19)
Age	1.19*** (0.05)	1.49*** (0.11)
Conservatism	1.01*** (0.02)	0.77*** (0.04)
Education	-0.28*** (0.05)	-0.42*** (0.11)
Occupational Importance of Programming	-0.56*** (0.05)	-0.17* (0.07)
Occupational Importance of Programming (lag 1)		-0.27*** (0.07)
Occupational Importance of Programming (lag 2)		-0.67*** (0.12)
Observations	100,914	28,905
Log Likelihood	-46,499.06	-12,101.85
Akaike Inf. Crit.	93,020.11	24,229.70
Bayesian Inf. Crit.	93,124.86	24,337.23

Note. Estimates are presented outside parentheses, and standard errors are presented inside parentheses. All occupational exposure variables have been standardized via z-scoring for presentation. * $p < .05$; ** $p < .01$; *** $p < .001$.

Exploring Possible Attrition Effects. The models depicted in our main text included all participants, regardless of how many time-points of the NZAVS they completed. To ensure that our effects were not driven by attrition effects, we re-estimated the relationship between occupational AI exposure and God belief with all covariates (see Table 3, Model 2) for participants who reported complete religion and occupation data for (a) at least two time-points, (b) at least three time-points, (c) at least four time-points, (d) at least five time-points, and (e) at least six time-points. Figure S4 shows the effect size of the key relationship between AI exposure and God belief in each of these models, and the error bars represent the standard error in the model. This Figure shows that the effect is statistically significant and similar in magnitude regardless of whether we rule out participants who participated in a smaller fraction of survey waves. We therefore consider it unlikely that attrition drove our findings.

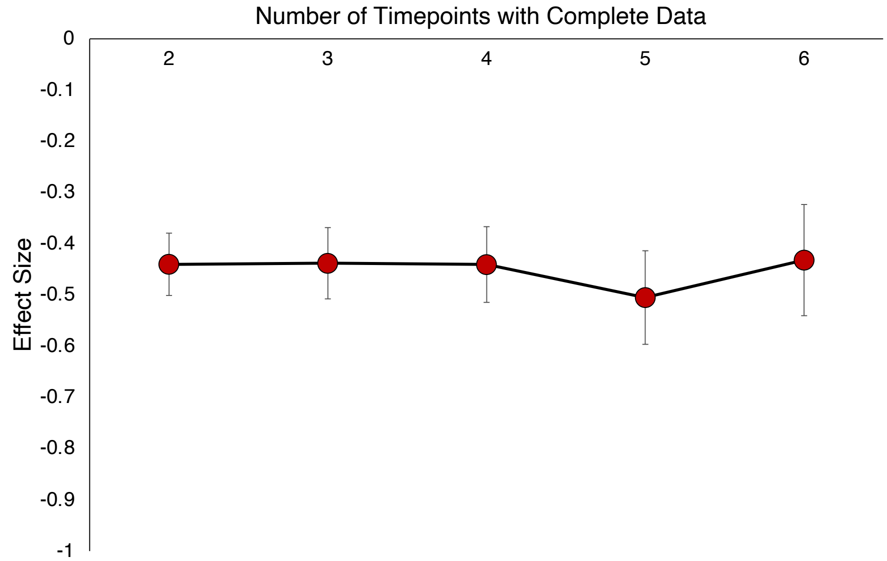

Figure S4. The relationship between AI exposure and God belief across participants who completed varying number of time-points. Nodes represent the effect size. Error bars represent standard error. These estimates control for age, gender, income, timepoint, political conservatism, and exposure to other scientific disciplines.

Ruling out Alternative Modeling Strategies in the Study 3 Dataset

We considered a multi-level modeling approach in which we interacted each person's mean AI exposure with survey timepoint. This approach would be similar to Studies 1-2, which tested whether countries and states with high levels of robotics experienced greater religious decline throughout the 21st century. However, the approach is less appropriate for Study 3 because countries and states almost never experience declining automation, whereas individuals frequently shift between jobs which have different levels of exposure to AI. This means that someone's mean level of AI exposure across the entire NZAVS survey is not a very informative statistic. We therefore considered it more appropriate to track how a person's occupational AI exposure at a given time-point *t* correlated with their religiosity at that time-point, and also their religiosity at future time-points in the survey using lagged terms. We also considered (and pre-registered as an alternative analysis) a cross-lagged panel model with random intercepts. However, this model did not converge, so we elected to use multi-level models (which we also pre-registered) to test our hypotheses

5. Supplemental Information for Study 4

Study 4 Workplace Behavior Measures

Our main text focuses on the measures in timepoint 1 (T1) and timepoint 2 (T2) which test our main hypothesis. But we also investigated the downstream consequences, measured in timepoint 3 (T3), of a negative association between automation and religiosity in our Study 4 dataset. Past research has linked religiosity to a host of positive outcomes. Studies on religion and social behavior have found that religious people often behave more prosocially (35,36) and honestly (37,38), and that they are trusted more than non-religious people (39,40). Other studies have described more cognitive correlates of religiosity, such as higher levels of self-control (41,42) and conscientiousness (43). If automation leads to religious decline, could it also encourage declines in these positive attributes?

We measured workplace behaviors that resembled outcomes previously linked to religiosity in previous research on religion and prosociality (35,39,44) (e.g., unethical behavior, trust, incivility, organizational citizenship behavior, which are face-valid indicators of prosociality) and on religion and cognitive control (41,42) (e.g., goal progress, task proficiency, which have been previously linked to self-control (45)). The fact that these measures were supervisor-reported helped mitigate self-report biases such as social desirability concerns (46). Finally, we measured age, gender, socioeconomic status, education, and tenure with the company as pre-registered covariates.

These workplace behavior measures are listed below, and Table S19 displays the descriptive statistics of all measures.

Goal Progress (T3). We used the Goal Progress scale developed by Wanberg, Zhu, & Van Hooft (47). Each participant was rated by their supervisor on a 1 (Strongly agree) - 5 (Strongly disagree) scale across 6 items, including "___ was productive at work" and "___made good progress at work". Each item started with "Over the last week" to make the scale sensitive to the context of the data collection.

Task Proficiency (T3). We used the Task Proficiency scale developed by Mitchell and colleagues (48). Each participant was rated by their supervisor on a 1 (Strongly agree) - 5 (Strongly disagree) scale across three items, including "___ carried out the core parts of his/her job well" and "___ completed his/her core tasks well using the standard procedures." Each item started with "Over the last week" to make the scale sensitive to the context of the data collection.

Organizational Citizenship Behavior (T3). We used the Organizational Citizenship Behavior scale developed by Lee and Allen (49). Each participant was rated by their supervisor on a 1 (Very low) to 7 (Very high) scale across three items, including "Overall level of effort of ___" and "Overall willingness to do what it takes to successfully complete assigned tasks of ___." Each item started with "Over the last week" to make the scale sensitive to the context of the data collection.

Counterproductive Workplace Behavior (T3). We used the Counterproductive Workplace Behavior scale developed by Bennett & Robinson (50). Each participant was rated by their supervisor on a 1 (Strongly disagree) to 5 (Strongly agree) scale across seven items from Bennett & Robinson's (2000) measure of counterproductive workplace behavior. Items highlighted various behaviors such as cursing, pranking, or publicly embarrassing colleagues for ethical failings at work.

Instigated Incivility (T3). We used the Instigated Incivility scale used in Koopman and colleagues (51). Each participant was rated by their supervisor on a 1 (Strongly disagree) to 5 (Strongly agree) scale across three items, including "___ put a co-worker down or acted condescendingly towards them" and "___ paid little attention to a coworker's statement or showed little interest in their opinion." Each item started with "Over the last week" to make the scale sensitive to the context of the data collection.

Unethical Behavior (T3). We used the Unethical Behavior scale used in Welsh, Bush, Thiel, and Bonner (52). Each participant was rated by their supervisor on a 1 (Strongly disagree) to 5 (Strongly agree) scale across four items, including "___cuts corners to complete work assignments more quickly" and "___ alters performance numbers to appear more successful." Each item started with "Over the last week" to make the scale sensitive to the context of the data collection.

Perceived Trust (T3). We used the Perceived Trust scale developed by Robinson (53). Each participant was rated by their supervisor on a 1 (Strongly disagree) to 5 (Strongly agree) scale across six items, including "I believed that ___ has high integrity" and "___ was open and upfront with me."

Table S19.
Descriptive Statistics for Variables in Study 4

Variable	**Mean**	**Standard Deviation**
Intrinsic Religiosity (T1)	3.13	.65
Religious Fundamentalism (T1)	3.35	.57
Occupational AI Exposure (T1)	3.05	.84
Religiosity (T2)	3.55	.81
Goal Progress (T3)	3.74	.69

Task Proficiency (T3)	3.67	.84
Organizational Citizenship Behavior (T3)	3.84	.59
Counterproductive Workplace Behavior (T3)	3.15	.89
Instigated Incivility (T3)	2.85	1.00
Unethical Behavior (T3)	2.48	.91
Perceived Trust (T3)	3.13	.50

Study 4 Full Multiple Regression Models

Our main text reports the results of regression models in which T1 AI exposure was negatively associated with T2 religiosity, even controlling for T1 religious fundamentalism and intrinsic religiosity. In Table S20, we summarize the full statistics associated with this relationship.

These models also found an interaction between T1 AI exposure and T1 intrinsic religiosity, such that the negative link between T1 AI exposure and T2 religiosity was stronger for participants who began the study lower in intrinsic religiosity compared to those who began the study higher in intrinsic religiosity. Table S19 displays the coefficients from these regression models. These models also control for age, gender, education, SES, and organizational tenure, which were our pre-registered covariates.

Table S20.
Full Coefficients for Study 4 Multiple Regression Models

	df	Adj. R^2	*b*(SE)	*β*	*t*	*p*
Model 1: Main Effects	229	.04				
AI Exposure			-.18 (.08)	-.19	-2.17	.03
Intrinsic Religiosity			.13 (.11)	.10	1.18	.24
Religious Fundamentalism			.08 (.09)	.06	.88	.38
Age			-.003 (.007)	-.03	-.46	.65
Gender			.04 (.11)	.03	.39	.70
Education			.06 (.06)	.07	1.04	.30
SES			< .001 (.02)	.002	.04	.97
Organizational Tenure			.01 (.03)	.03	.38	.70
Model 2: One Interaction	229	.06				
AI Exposure			-.19 (.08)	-.20	-2.30	.02
Intrinsic Religiosity			.14 (.11)	.11	1.31	.19
Religious Fundamentalism			.08 (.09)	.06	.91	.37
Age			-.004 (.006)	-.04	-.60	.55
Gender			.04 (.11)	.02	.35	.73
Education			.05 (.06)	.05	.80	.42
SES			-.001 (.02)	-.004	-.06	.95
Organizational Tenure			.02 (.03)	.05	.63	.53
AI Exposure * Intrinsic Religiosity			.18 (.08)	.14	2.19	.03
Model 3: Both Interactions	227	.06				
AI Exposure			-.17 (.08)	-.18	-2.06	.04
Intrinsic Religiosity			.15 (.10)	.12	1.44	.15
Religious Fundamentalism			.09 (.09)	.06	.95	.35
Age			-.004 (.007)	-.05	-.64	.53
Gender			.03 (.11)	.02	.26	.80
Education			.05 (.06)	.05	.82	.41
SES			-.001 (.02)	-.002	-.03	.97
Organizational Tenure			.02 (.03)	.05	.69	.49
AI Exposure * Intrinsic Religiosity			.17 (.08)	14	2.10	.04
AI Exposure *			.14 (.11)	.08	1.28	.20

Religious Fundamentalism

Study 4 Supplemental Measures

With these data, we were able to test whether AI-linked declines in religiosity predict subsequent variation in workplace behaviors. We did this using a structural equation model. We began by modeling the pre-registered mediation dynamic (AI exposure → religiosity → workplace behaviors) and then adding additional paths using a data-driven approach with modification indices. We also chose to incorporate intrinsic religiosity as a moderator of the AI exposure → religiosity path given the significant interaction we observed in our initial models.

Table S21 summarizes the model-building process. Model 1 was our original model, which only modeled the relationship between AI exposure and religiosity, the interaction between AI exposure and intrinsic religiosity on religiosity, and the relationships between religiosity and workplace behaviors. This model showed poor initial fit, with a significant chi-squared statistic, CFI and TLI values below .95, and an RMSEA value above .05. We used modification indices in a data-driven approach which identified the paths which would improve model fit if they were included in the equation. These included (a) adding a relationship between intrinsic religiosity and organizational citizenship behavior (MI = 15.75), (b) adding a relationship between AI exposure and unethical behavior (MI = 16.19), (c) adding a relationship between AI exposure and trust (MI = 7.61), and (d) adding a relationship between AI exposure and task proficiency (MI = 7.70). Every MI-derived pathway resulted in significant improvement in model fit, as estimated through likelihood ratio tests which produced significant improvements in chi-squared fit. The final model (Model 5) showed no modification indices above 5.00 and showed good model fit across all fit statistics. Table S22 summarizes the variances and covariances in this final model.

Table S21.
Model-Building in Study 4

Model	**DF**	**Chi Squared**	**Δ Chi Squared**	**CFI**	**TLI**	**RMSEA**	**Largest MI**
1	56	χ^2= 111.52, p < .001		.81	.69	.07	Intrinsic Religiosity → Org. Citizen. Behavior
2	55	χ^2= 90.07, p = .002	χ^2= 21.45, p < .001	.88	.80	.05	AI Exposure → Unethical Behavior
3	54	χ^2= 71.61, p = .06	χ^2= 18.47, p < .001	.94	.90	.04	AI Exposure → Trust
4	53	χ^2= 63.39, p = .16	χ^2= 8.22, p = .004	.97	.94	.03	AI Exposure → Task Proficiency
5	52	χ^2= 55.38, p = .35	χ^2= 8.00, p = .005	.99	.98	.02	None above 5.00

Table S22.
Variances Covariances in Final Study 4 Model

Statistic	**Variable**	**Estimate (SE)**	***p*-value**
Variances	Religiosity	.60 (.06)	< .001
	Organizational Citizenship Behavior	.30 (.04)	< .001
	Goal Progress	.45 (.04)	< .001
	Counterproductive Workplace Behaviors	.71 (.06)	< .001
	Instigated Incivility	.95 (.07)	< .001
	Unethical Behavior	.59 (.06)	< .001
	Task Proficiency	.65 (.06)	< .001
	Trust	.24 (.02)	< .001
Covariances	Organizational Citizenship Behavior ~~		
	Goal Progress	.03 (.03)	.22
	Counterproductive Workplace Behaviors	-.06 (.03)	.05
	Instigated Incivility	-.13 (.03)	.001
	Unethical Behavior	-.07 (.03)	.02
	Task Proficiency	.04 (.03)	.21

Trust	.009 (.02)	.60
Goal Progress ~~		
Counterproductive Workplace Behaviors	-.07 (.04)	.07
Instigated Incivility	-.08 (.04)	.05
Unethical Behavior	-.07 (.03)	.05
Task Proficiency	.02 (.04)	.52
Trust	-.002 (.02)	.91
Counterproductive Workplace Behaviors ~~		
Instigated Incivility	.12 (.06)	.04
Unethical Behavior	.25 (.05)	< .001
Task Proficiency	-.06 (.05)	.20
Trust	.09 (.03)	.003
Instigated Incivility ~~		
Unethical Behavior	.19 (.05)	< .001
Task Proficiency	-.06 (.05)	.27
Trust	.03 (.03)	.30
Unethical Behavior ~~		
Task Proficiency	-.18 (.04)	< .001
Trust	.04 (.03)	.09
Task Proficiency ~~		
Trust	.002 (.03)	.94

This SEM (see Figure S5) reproduced the negative lagged association between T1 AI exposure and T2 religiosity, as well as the moderation by T1 intrinsic religiosity. It also reproduced many of the associations documented in previous research involving prosociality and cognitive control. Religiosity was positively associated with organizational citizenship behavior, goal progress, and task proficiency, and was negatively associated with counterproductive workplace behavior, unethical behavior, and incivility. Past studies have shown that religious people can show pronounced social desirability biases in self-report surveys (54), but we measured T3 workplace behavior using supervisor-report, increasing the dependability of these associations.

Our model also revealed two unexpected findings. First, we found that T2 religiosity was not associated with T3 perceived trust. Previous research on religion and trust has sampled people living in religious communities (39,55) whereas our sample of employees in a manufacturing plant may not have relied on religion to the same extent to gauge trust. Second, AI exposure was linked to T3 supervisor-reports of higher perceived trust, task proficiency, and lower unethical behavior. This suggests that, at least in the workplace, adopting AI technology can carry benefits, leading employees to be perceived as more proficient, ethical, and trustworthy. However, AI exposure showed no significant association with supervisor-reports of workplace behaviors, such as organizational citizenship, goal progress, counterproductive workplace behavior, or incivility, suggesting that it had a narrower range of benefits compared to religious belief. Table S22 summarizes these statistics in full.

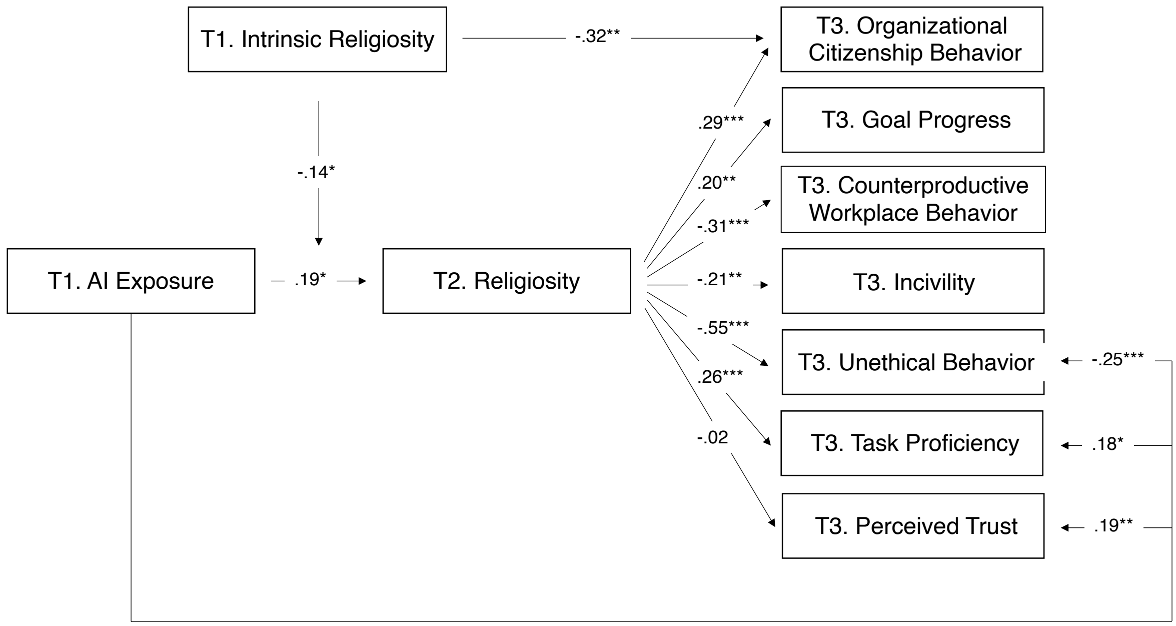

Figure S5. A Structural Equation Model Displaying Study 4 Results. AI exposure and intrinsic religiosity have been centered. Coefficients have been standardized and can be interpreted as effect sizes. Variances and covariances are not shown here for display purposes, but they are listed in Table S22. This model includes covariates (age, gender, SES, education, tenure in organization) which are omitted for display purposes. * $p < .05$; ** $p < .01$; *** $p < .001$.

6. Supplemental Information for Study 5

Stimuli in Study 5

In our main text Methods, we summarize the experimental design of Study 5, which involved reading about three innovations in language, medicine, and agriculture. Table S23 summarizes the paragraphs that participants read about each advance, and provides a link to the source of each paragraph. Some paragraphs have been slightly adapted for spelling, grammar, and length.

Table S23.
Stimuli in Study 5

Condition, Domain	**Text, Source**
AI, Language	ChatGPT is a natural language processing tool that allows users to have human-like conversations with an AI chatbot. Users can ask all kinds of questions to ChatGPT to get straightforward and uncluttered responses in return. For example, you can use the tool as an encyclopedia and ask questions. For instance, “define Newton’s laws of motion” or “write a poem,” which it will do instantly. Additionally, you may ask ChatGPT to design a computer program which performs simple or complex tasks such as solving anagrams or detecting animals using data about their average height and weight. ChatGPT is so good at emulating human language that many people cannot distinguish between ChatGPT and written responses by real people. Source: https://emeritus.org/blog/ai-ml-what-is-chatgpt/
AI, Medicine	Sharing medical data between laboratories and medical experts is important for medical research. However, data sharing is often sufficiently complex

	and sometimes even impossible due to the strict data regulatory legislation in Europe. Researchers addressed the problem and developed an artificial neural network that creates synthetic x-ray images that can fool even medical experts. Source: https://www.sciencedaily.com/releases/2022/11/221117102821.html
AI, Agriculture	Internet of Things (IoT) is a new method of giving physical objects "minds," with sensors, memory, processing ability, and communication ability. These devices can communicate with each other, adapt their behavior, and predict the future without an internet connection. IoT is revolutionizing agriculture because it allows surveillance cameras, tractors, sprinklers, and other agricultural tools to exchange data on temperature, humidity, waste, wind speed, and pest infestation in order to control plant treatment (e.g., including pesticide control and water volume) without farmers actively making decisions. Source: https://www.forbes.com/sites/louiscolumbus/2021/02/17/10-ways-ai-has-the-potential-to-improve-agriculture-in-2021/?sh=3f5727f17f3b
Science, Language	Over 70 million deaf people use sign languages as their preferred communication form. Although they access similar brain structures as spoken languages, it hasn't been identified the brain regions that process both forms of language equally. Scientists have now discovered that Broca's area in the left hemisphere, central for spoken languages, is also crucial for sign languages. This is where the grammar and meaning are processed, regardless of whether it is spoken or signed language. Source: https://www.sciencedaily.com/releases/2022/12/221220112426.htm
Science, Medicine	Fewer cases of melanoma were observed among regular users of vitamin D supplements than among non-users, a new study finds. People taking vitamin D supplements regularly also had a considerably lower risk of skin cancer, according to estimates by experienced dermatologists. The study included nearly 500 people with an increased risk of skin cancer. Source: https://www.sciencedaily.com/releases/2023/01/230109112555.htm
Science, Agriculture	A research group is studying how plants 'breathe'. They have gained new insights into how grasses develop efficient 'breathing pores' on their leaves. If important landmark components in this development process are missing, the gas exchange between plant and atmosphere is impaired. These findings could nonetheless be relevant to improving agricultural crops. Source: https://www.sciencedaily.com/releases/2022/12/221223103421.htm

Robustness Analyses for Study 5

Here we report two robustness analyses for Study 5. The first series of analyses reports the main effects of Study 5 without controlling for perceived impressiveness and technological sophistication. Our second series of analyses reports the main effects of Study 5 without including participants from our pilot data. Results were substantively identical to our main text analyses in both cases.

Without controlling for impressiveness and technological sophistication, participants viewed AI advances as less associated with laws of nature than scientific innovations, $b = -1.44$, $SE = 0.07$, $t = -20.59$, $p <$

0.001, *95% CIs* [-1.58, -1.30]. We also found that participants reported less religious conviction in the AI condition vs. the science condition, $b = -0.43$, $SE = 0.09$, $t = -4.90$, $p < 0.001$, *95% CIs* [-0.61, -0.26].

When excluding subjects from our pilot study, participants viewed AI advances as less associated with laws of nature than scientific innovations, $b = -1.63$, $SE = 0.09$, $t = -17.95$, $p < 0.001$, *95% CIs* [-1.81, -1.45]. We also found that participants reported less religious conviction in the AI condition vs. the science condition, $b = -0.73$, $SE = 0.12$, $t = -6.24$, $p < 0.001$, *95% CIs* [-0.95, -0.50].

7. Study S1

We ran this study during a 7-hour MBA seminar in Singapore, in which senior executives from Taiwan learned about workplace applications of AI. The module introduced easy-to-use computing techniques in R and Python for implementing AI machine learning solutions. We randomly assigned participants to either the control or experimental condition. Participants in the control condition ($n = 35$) received their questions at the beginning of the seminar (before AI exposure); participants in the experimental condition ($n = 43$) received their questions at the end of the seminar (after AI exposure). Among participants who reported their gender, there were 27 men and 30 women, and a median age of 40 – 50.

The first questions in the survey were a manipulation check measuring whether attending the seminar actually increased confidence in automation (we reasoned that even anticipating the seminar could increase these perceptions). Participants separately rated the promise of automation (AI and robotics), medicine, biology, chemistry, and mathematics with a 1 (“No Promise”) – 7 (“Very Promising”) scale. Participants then rated three “playing God” items using a 1 (“Strongly Disagree”) – 7 (“Strongly Agree”) scale. These items were: (a) Artificial intelligence and robotics allow humans to “break” the laws of nature, (b) Artificial intelligence and robotics allow humans to do things that we have never been able to do before, (c) Artificial intelligence and robotics give humans “superhuman” abilities. Finally, participants rated three items measuring religiosity: (a) Belief in God has an important role in the workplace, (b) Prayer has an important role in the workplace, and (c) Religious service attendance has an important role in the workplace. Participants also reported their religious identity and rated the importance of religion in their life using a 1 (Not at all Important) – 7 (Very Important) scale during the demographics section of the survey.

The manipulation succeeded such that participants in the AI condition rated AI as more promising for the future than participants in the control condition, $b = 0.38$, $SE = 0.17$, $t = 2.19$, $p = 0.03$, but did not rate any other scientific discipline as more promising for the future (*p*s > 0.05). The manipulation also increased participants’ confidence that they could “play God” with AI technology. Participants in the experimental condition agreed significantly more with the items “Artificial intelligence and robotics allow humans to “break” the laws of nature,” $b = 1.18$, $SE = 0.44$, $t = 2.67$, $p = 0.009$, “Artificial intelligence and robotics allow humans to do things that we have never been able to do before,” $b = 0.93$, $SE = 0.32$, $t = 2.93$, $p = 0.005$, and marginally more with the item “Artificial intelligence and robotics give humans ‘superhuman’ abilities,” $b = 0.64$, $SE = 0.36$, $t = 1.79$, $p = 0.08$. See Figure S6 for an illustration of these effects.

There was no significant main effect of experimental condition on any of the three religion items (*p*s > 0.05). However, condition interacted with religious importance on ratings of prayer, $b = -0.52$, $SE = 0.17$, $t = -3.00$, $p = 0.004$, and service attendance, $b = -0.55$, $SE = 0.17$, $t = -3.22$, $p = 0.002$. For participants who rated religion as not at all important in their life, the AI seminar did not have a significant effect on these items (*p*s > 0.05). But for participants who rated religion as very important in their life, the AI seminar decreased perceived importance of prayer at work, $b = -0.82$, $SE = 0.32$, $t = -2.57$, $p = 0.01$, and service attendance at work, $b = -1.00$, $SE = 0.31$, $t = -3.22$, $p = 0.002$. Figure S6, breaks down the effect of condition at each level of religious importance to display this moderation.

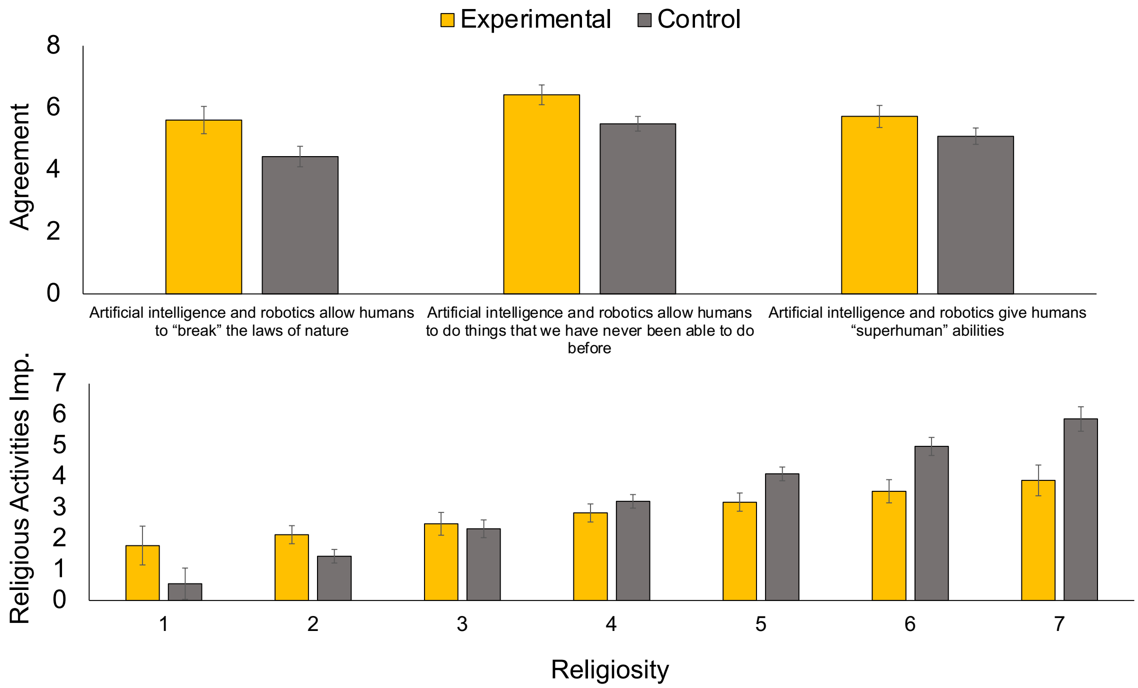

Figure S6. Top) Estimates of playing God items in the control and experimental conditions from a general linear model. Bottom) Estimates of religious activities (prayer and service attendance) importance in the workplace from a general linear model where condition is moderated by religiosity. We present prayer and services together because their effects were nearly identical.

In sum, this field experiment showed that exposure to AI through an intensive one-day seminar increased senior business executives' belief that artificial intelligence allows humans to "play god," break the laws of nature, and do things that humans have never done before. Among highly religious individuals, exposure to AI also decreased the importance of prayer and service attendance for workplace behavior, although it did not change perceptions of God's importance. Nevertheless, the items measuring prayer and service attendance are interesting in their own right, given these are two forms of petitionary religious appeals.

Despite this study's small sample, it offers valuable evidence that automation leads people to feel unconstrained by laws of nature, and that exposure to automation may reduce people's perceived importance of religious appeals—at least among the highly religious.

8. Study S2a-b

In two highly related supplemental studies (Studies S2a-b), we examined the cross-sectional relationship between AI favorability and religiosity in two different datasets. We reasoned that non-religious people would be more favorable towards automation than religious people for at least two reasons. First, favorability towards automation may lead to religious decline (producing a negative correlation with religiosity). Second, religious people may perceive automation as more of a threat to their worldview than non-religious people.

We examined this relationship with two datasets. The first "international" dataset (Study S2a) consisted of data collected by the Pew Research Center between 2019-2020 from 32,330 people (16,890 men, 15,440 women; M_{age} = 48.45, SD_{age} = 18.12) across Australia, Brazil, Canada, Czech Republic, France, Germany, India, Italy, Japan, Malaysia, the Netherlands, Poland, Russia, Singapore, South Korea, Spain, Sweden, Taiwan, United Kingdom, and the United States. Table S24 displays the religious demographic of the sample. In this dataset, not all participants answered all questions (some participants indicated responses of “don’t know” or “no opinion” which were scored as missing in our analyses), so degrees of freedom vary across analyses.

Table S24.
Religious Identification of Participants in the Study S2a

Country	Christian	Muslim	Baha’i	Hindu	Buddhist	Sikh	Jewish	None	Other
Australia	726	23	2	30	26	2	3	611	99
Brazil	1257	0	0	0	0	0	1	102	114
Canada	880	34	0	21	13	15	23	438	90
Czech Republic	470	0	0	0	3	0	3	883	24
France	719	76	0	0	13	0	7	580	26
Germany	849	42	0	0	9	0	2	581	16
India	76	275	0	2675	41	54	0	9	20
Italy	1124	16	0	2	0	0	0	289	43
Japan	21	1	0	1	548	0	0	894	5
Malaysia	146	1144	1	75	228	2	0	30	16
Netherlands	636	38	0	11	21	0	2	712	75
Poland	1386	0	0	0	0	0	0	71	11
Russia	1031	148	0	0	3	0	0	340	185
Singapore	347	142	0	142	375	0	1	393	58
South Korea	533	0	0	0	249	0	0	771	9
Spain	827	16	0	0	0	0	1	244	41
Sweden	869	22	0	0	0	0	0	615	59
Taiwan	163	1	0	0	518	0	0	384	484
United Kingdom	731	62	0	12	11	7	3	606	33
United States	923	8	0	8	7	0	50	337	103

Note. Values marked “NA” were not read to participants. “Christian” includes participants who reported being Roman Catholics, Protestants, Orthodox, and “just a Christian.” “None” includes participants who reported being Atheists, Agnostics, and “Nothing in Particular.” Participants who refused to answer the question or answered “Don’t Know” are not included in this table.

The second “USA” dataset (Study S2b) consisted of publicly available data collected by the Pew Research Center in 2017 which comprised of 4,135 people from the United States (2,046 men, 2,089 women; 463 participants aged 18-29, 1177 aged 30-49, 1331 aged 50-64, 1160 aged 65+; 2,648 Christians, 92 Mormons, 143 Jews, 29 Muslims, 33 Buddhists, 27 Hindus, 1,069 Non-Religious, 1 refused to answer). This survey also included information about political party lean (772 people leaned Republican, 714 people leaned Democrat) and college attainment (2,183 participants had earned their college degree).

Both datasets contained measures of people’s AI favorability. In the international dataset, participants rated whether (a) robots and (b) AI was a good or bad thing for society using a binary scale. We chose to average these responses into a composite variable because the responses to the two items also correlated strongly, $r(25{,}102) = .45$, $p < .001$, and using a composite of the two items gave us more statistical power than if we had used either item in isolation since participants did not always respond to all items. In the USA dataset, participants rated their enthusiasm about “the possibility that computers and robots could do most of the work currently done by humans,” using a scale of 1-4 anchored at 1 (“Very enthusiastic”) and 4 (“Not at all enthusiastic”). We reverse-scored this item so that higher values represented greater enthusiasm.

Both datasets also contained measures of religiosity. In the international dataset, participants responded to the item “how important is religion in your life,” which was rated on a 1-4 scale anchored at 1 (“Very Important”) to 4 (“Not at all important”). We reverse-scored the scale so that higher values represented greater importance. In the USA dataset, participants rated their frequency of service attendance using a

1-6 scale ranging from “never” to “more than once per week.” These different measures allowed us to test how attitudes towards AI were linked to religious behaviors as well as self-reported religious importance.

Our international dataset also allowed us to measure people’s favorability towards science more generally, and other technological innovations using the same binary scale that they used to rate robots and AI. Specifically, participants rated their favorability towards science with the item “Overall, would you say developments in science have had a mostly ____ effect on society?” with response options ranging from (1) mostly positive effect, (2) mostly negative effect, and (3) equal positive and negative effects. We recoded these options so that values were ordered in terms of positivity, which 3 representing “mostly positive effect” and 1 representing “mostly negative effect.”

How did people’s attitudes about AI relate to their religiosity? A zero-order correlation found that AI favorability was negatively linked with religiosity in the international dataset, $r(30,202) = -.08$, $p < .001$. This negative correlation remained after controlling for sex, age, favorability towards science, and favorability towards space travel in a regression model where intercepts randomly varied across nations (Table S25, Model 1). Favorability towards science was negatively associated with religiosity, but its association was far weaker than the negative association between AI favorability and religiosity. Favorability towards space travel was *positively* associated with religiosity in the model. Similarly, in the USA dataset, AI favorability was negatively associated with religiosity, $r(4,110) = -.09$, $p < .001$, and this negative association persisted controlling for age, gender, education, and political orientation (Table S25, Model 2). Participants from around the world and across the United States with more favorable attitudes towards AI had lower levels of religiosity, and this association could not be reduced to education, age, gender, political orientation, or favorability towards science and technology.

Table S25.
AI Favorability and Religiosity Across Individuals Around the World and in the USA

Model | Predictor	*b (SE)*	*β*	*t*	*p*	95% LLCI	95% ULCI
International Dataset (Study S2a)						
AI Favorability	-.16 (.016)	-.06	-10.18	< .001	-.20	-.13
Male	-.17 (.01)	-.07	-13.49	< .001	-.20	-.15
Age	.008 (.0004)	.12	20.96	< .001	.007	.008
Science Favorability	-.02 (.01)	-.01	-2.18	.03	-.04	-.002
Space Favorability	.04 (.02)	.01	2.16	.03	.004	.08
USA Dataset (Study S2b)						
AI Favorability	-.21 (.06)	-.10	-3.74	< .001	-.32	-.10
Male	.12 (.04)	.07	2.94	.003	.04	.20
Age	-.27 (.09)	-.08	-3.06	.002	-.44	-.10
College Education	.15 (.09)	.05	1.77	.08	-.02	.32
Republican	.80 (.09)	.24	9.28	< .001	.63	.97

Note. The Study S2a model comes from a multilevel model with intercepts varying randomly across nations. The Study S2b model comes from a general linear model of American participants. Predictors are indented below model titles.

9. Study S3

In Study S3, we tested whether religious individuals perceived religion and automation as compatible. A well-established finding in research on science and religion is that religious people view science and religion as highly compatible (56,57). This is because people view science and religion as fulfilling different capacities and meeting different needs. Science involves the human exploration and application of laws of nature, whereas religion involves “supernatural” agents and principles that transcend these laws (58)[1]. We predicted that, because many people also believe that automation can operate outside

[1] This distinction between the “natural” and “supernatural” is often fuzzy in practice, because people view gods and spirits as exercising their supernatural powers through nature (59). However, many cultures

these laws of nature, religious people would view religion as less compatible with automation than science.

We designed a pre-registered within-subjects experiment in which 498 religious individuals rated AI, robotics, and other branches of science (biology, chemistry, mathematics, medicine, the same disciplines that we measured in Study 3) on 12 bipolar and unipolar items: The bipolar items were (1) "The field of ___ is focused on HOW [vs. WHY] to solve problems" (2) "The field of ___ is focused on concrete observable information [vs. abstract ideas and principles]," and (3) "The field of ___ is focused on abstract ideas and principles [vs. intuition]." The unipolar items, anchored at 1 ("Strongly Disagree") and 7 ("Strongly Agree"), were (4) "The field of ___ involves agents with cognitive or physical abilities that surpass human abilities," (5) "People who work in ___ are playing God," (6) "People who work in ___ are doing things that should be left to God," (7) "The field of ___ involves providing social support to people," (8) "The field of ___ involves providing connection to a community," (9) "The field of ___ involves applying laws of nature," (10) "The field of ___ involves discovering laws of nature," (11) "God works through ___ ," (12) "Religion is compatible with ___."

We pre-registered five latent factors underlying these items, and a promax factor analysis suggested that five factors each explained > 10% of variance in the items, with a cumulative variance explained of 69%. As pre-registered, there was a construal level factor (items 1-3), a playing god factor (items 4-6), a communality factor (items 7-8), a laws of nature factor (items 9-10), and a compatibility with religion factor (items 11-12). All item loadings were greater than .30, with no cross-loadings above .30. We averaged the items into these five indices for analyses.

After computing these indices, we fit a multilevel model in which each dimension was regressed on discipline dummy-codes, contrasted against automation (the average score of AI and robotics). We combined robotics and AI into a single index for the sake of parsimony, but it had little impact on our findings: Our results replicated regardless of whether we modeled robotics or AI individually.

Our first model found that people rated automation as less compatible with religion than all other scientific disciplines (see Table S26). We next investigated the possible mechanisms of this effect by examining whether automation was unique from all other disciplines in other respects. Our models showed that automation was not viewed as significantly different from other disciplines in terms of prosociality, or construal level (*p*s > .10). However, automation was seen as less associated with laws of nature compared to any other scientific discipline. Automation was also seen as significantly more associated with playing God than all other disciplines. Statistics from these key models are displayed in Table S26.

Table S26.
Key Properties of Automation vs. Scientific Disciplines in Study S3

Outcome, Contrast	*b*	*SE*	*t*	*p*	95% CIs
Compatible With Religion					
Biology vs. Automation	1.07	0.06	19.29	< 0.001	0.96, 1.18
Chemistry vs. Automation	0.82	0.06	14.73	< 0.001	0.71, 0.92
Mathematics vs. Automation	0.62	0.06	11.27	< 0.001	0.52, 0.73
Medicine vs. Automation	1.38	0.06	24.84	< 0.001	1.27, 1.49
Associated With Laws of Nature					
Biology vs. Automation	1.38	0.06	21.94	< 0.001	1.26, 1.51
Chemistry vs. Automation	1.15	0.06	18.19	< 0.001	1.02, 1.27
Mathematics vs. Automation	0.20	0.06	3.22	0.001	0.08, 0.33
Medicine vs. Automation	1.30	0.06	20.69	< 0.001	1.18, 1.43
Encourages Playing God					
Biology vs. Automation	-0.58	0.04	-13.19	< 0.001	-0.67, -0.50
Chemistry vs. Automation	-0.66	0.04	-15.04	< 0.001	-0.75, -0.57

appear to hold the belief that God(s) can regularly violate laws of physics, biology, psychology, and chemistry that regulate the natural world (13).

Mathematics vs. Automation	-0.97	0.04	-21.90	< 0.001	-1.05, -0.88
Medicine vs. Automation	-0.44	0.04	-9.90	< 0.001	-0.52, -0.35

Note. Beta coefficients represent the mean difference between ratings of automation vs. other disciplines on 1-7 scales, which we describe in the Methods.

In sum, religious people perceived religion as less compatible with automation than with science. These perceptions were partly explained by the view that automation is less associated with laws of nature and that it encourages people to play God. This study supports our finding from Studies S2a-b that religious people feel more negative towards automation than other scientific disciplines, partly because automation gives people capacities that have historically been unique to God.

10. Study S4

Study S4 explored a different mechanism by which automation could lead to religious decline. In our introduction, we focus on how people may see automation as filling the same functional niche as supernatural agents. But it is possible that automation does not lead to religious decline because of functional overlap between automation agents and gods, but simply because of the lifestyles, activities, and challenges that are inherent to working in AI and robotics occupations. Working in AI and robotics may involve challenges that require more concrete (vs. abstract) construal, and lead people to reflect less on their religious values and supernatural beliefs compared to working in other scientific disciplines. We tested this hypothesis with a correlational study.

We ran a pre-registered study in which we asked 196 participants from Amazon Mechanical Turk to rate whether 21 activities were characteristic of AI, medicine (a science control), and telecommunications technology (a technology control). Participants responded to the prompt, "consider the functions of _______. When you use ________, what kinds of challenges are you most frequently trying to solve" using a 1 ("Very Rarely") – 7 ("Very Frequently"). We also asked a separate sample of 199 religious participants from Amazon Mechanical Turk to rate the same activities using the prompt "What kinds of challenges lead you to feel that religion is important in your life" using a 1 ("Not at All") – 7 ("Very Much") scale. The challenges in this study are listed in Table S27.

Table S27.
Items in Study S4

1. Providing connection to a community
2. Providing social support
3. Providing affiliation with others
4. Answering questions about right and wrong
5. Helping to navigate moral issues
6. Trying to live an ethical life
7. Making sense of the world
8. Explaining things that are hard to understand
9. Predicting things that will happen in the near future
10. Solving logistical problems
11. Helping with daily tasks
12. Assisting with your work
13. Making you feel better
14. Providing a sense of comfort
15. Making life easier
16. Helping you discover new things
17. Teaching you about the world
18. Assisting you with learning
19. Performing manual labor
20. Storing things in memory
21. Problem-solving

Challenges associated with AI were negatively associated with likelihood of inspiring religious devotion (henceforth called "religious importance"). For example, challenges such as "answering questions about right and wrong" (M_{AI} = 3.27, M_{REL} = 5.04), and "making sense of the world" (M_{AI} = 3.67, M_{REL} = 5.29) had among the strongest associations with religious importance and the least strong associations with AI. In contrast, "making life easier" (M_{AI} = 3.56, M_{REL} = 4.66), and "assisting with your work" (M_{AI} = 3.27, M_{REL} = 3.65) had among the strongest associations with AI and the least strong associations with religious importance. Whereas association with AI was negatively correlated with religious importance, r = -.51, p = .02, association with telecommunications technology was not significantly correlated with religious importance, r = -.05, p = .83, and association with medicine was positively correlated with religious importance, r = .43, p = .05. These associations are displayed in Figure S7.

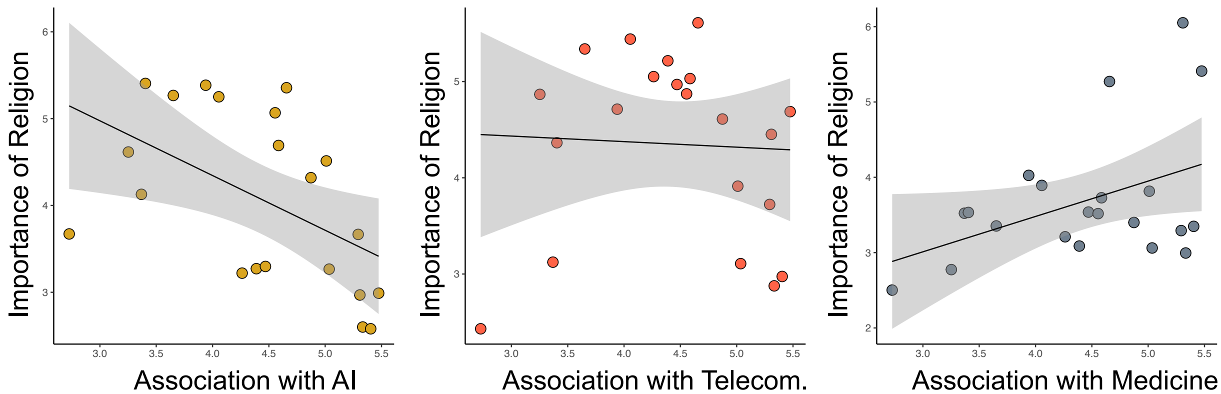

Figure S7. Nodes represent challenges, and the trendline represents the relationship between these challenges' associations with different disciplines and their likelihood of inspiring religious devotion. The error shading represents standard error around these relationships.

These findings suggest that the problems people face when working with automated agents may be uniquely unlikely to inspire religious devotion or strengthen people's religious conviction. This may be one reason why Studies 3-4 (main text) found that exposure to AI professions is associated with more religious decline than exposure to other scientific disciplines.

11. Study S5

Our main text shows that entering a profession in AI is associated with greater religious decline than entering a profession in another scientific field like medicine. In a final pre-registered supplemental study, we tested whether participants could anticipate this religious decline if religious individuals imagined entering an AI-focused occupation vs. an occupation in medicine.

We recruited 402 religiously identified participants for this study using Amazon Mechanical Turk through the CloudResearch platform. Participants in this study were told to imagine that they were accepting a job either in AI or in medicine, with the following prompts:

> ***AI Condition.*** We would like you to imagine that accepting a new job in **computer science** where you frequently use **artificial intelligence**. What kinds of activities do you think you would engage in as part of this job?
>
> ***Medicine Condition.*** We would like you to imagine that accepting a new job in **medicine** where you frequently use **tools of modern medicine**. What kinds of activities do you think you would engage in as part of this job?

Participants were then told that they would be involved in three different activities as part of this new job: (1) diagnosing illnesses faster, (2) developing new medication, and (3) creating treatment plans. We selected these activities because they are obviously in the domain of medicine, but they also have experienced high levels of AI infiltration in recent years.

For each activity, participants responded to the item “using AI [medicine] to solve this problem would strengthen my religious conviction” suing a 1 (“Would Not Strengthen”) – 9 (“Would Strengthen”) scale. After rating the individual activities, participants also responded to the general item: “As part of your job in _____ [AI/Medicine], how important of a role do you think that religion would play in your life” using a 1 (“Not Important”) to 7 (“Very Important”) scale.

Participants in the AI condition anticipated less religious conviction when evaluating disease diagnosis, $b = -1.15$, $SE = 0.27$, $t = -4.23$, $p < 0.001$, medicine development, $b = -1.33$, $SE = 0.27$, $t = -5.04$, $p < 0.001$, and treatment plan creation, $b = -1.11$, $SE = 0.27$, $t = -4.17$, $p < 0.001$. Participants also anticipated that they would be less religious upon entering AI vs. medicine, $b = -0.67$, $SE = 0.25$, $t = -2.70$, $p = 0.007$.

This study therefore provides evidence that participants are aware that entering an occupation involving automation might prompt less religiosity. Could this mean that our prior studies involved selection effects, such that non-religious people were simply selecting into AI professions? We find this possibility plausible as a partial explanation of our results, but not a complete explanation. In Study 3, change in religiosity happened within individual over time: working in AI was associated with decreased religiosity over time in the same people. Similarly, participants in Study 4 did not select into working with AI: they were assigned more AI work as their organization integrated AI technology.

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